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Decision-Making in Production Network Configuration

A Design Framework for Digital Twins of Global Production Networks

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Decision-Making in Production Network Configuration
-
A Design Framework for Digital Twins of Global Production Networks

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Institut für Produktionstechnik

Vorwort des Herausgebers

Die schnelle und effiziente Umsetzung innovativer Technologien wird vor dem Hintergrund der Globalisierung der Wirtschaft der entscheidende Wirtschaftsfaktor für produzierende Unternehmen. Universitäten können als "Wertschöpfungspartner" einen wesentlichen Beitrag zur Wettbewerbsfähigkeit der Industrie leisten, indem sie wissenschaftliche Grundlagen sowie neue Methoden und Technologien erarbeiten und aktiv den Umsetzungsprozess in die praktische Anwendung unterstützen.

Vor diesem Hintergrund wird im Rahmen dieser Schriftenreihe über aktuelle Forschungsergebnisse des Instituts für Produktionstechnik (wbk) am Karlsruher Institut für Technologie (KIT) berichtet. Unsere Forschungsarbeiten beschäftigen sich sowohl mit der Leistungssteigerung von additiven und subtraktiven Fertigungsverfahren, den Produktionsanlagen und der Prozessautomatisierung sowie mit der ganzheitlichen Betrachtung und Optimierung der Produktionssysteme und -netzwerke. Hierbei werden jeweils technologische wie auch organisatorische Aspekte betrachtet.

Prof. Dr.-Ing. Jürgen Fleischer

Prof. Dr.-Ing. Gisela Lanza

Prof. Dr.-Ing. habil. Volker Schulze

Prof. Dr.-Ing. Frederik Zanger

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Vorwort des Verfassers

Die vorliegende Arbeit entstand während meiner Tätigkeit am wbk Institut für Produktionstechnik des Karlsruher Instituts für Technologie.

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Abschließend möchte ich meinen Eltern, meinem Bruder und meinen Stiefeltern für ihre stete Unterstützung über viele Jahre hinweg danken. Mein größter Dank gilt aber dir, Mareike, du warst mit deiner Energie, deiner Geduld und nicht zuletzt deiner Entschlossenheit, mich nicht vom Weg abkommen zu lassen, das Fundament dieser Arbeit.

Karlsruhe am 6. Oktober 2025

Martin Benfer

You must learn to run before you can learn to walk.

Marc Raibert

Abstract

The configuration of production networks is now as complex and volatile a task as ever. Making the correct decisions in today's competitive and disruption-prone environment requires adequate tools that combine data from different sources and offer decision support for the multitude of configuration tasks. However, many companies still rely on largely manual decision-making or case-by-case modelling, leading to slower and worse decisions. How companies can best create a decision support system that is a digital twin of their production network remains a question.

This thesis seeks to provide companies with a path towards such a system. Thus, it interrogates the question: *How can decision support systems for the configuration of global production networks be realised efficiently, requiring reduced efforts for each decision and thus enabling faster and better decision-making?*

A design science research methodology focused on the pragmatic utility of the developed artefact is applied to address the question.

The artefact developed in response to the research question is a framework for designing global production network twins. It comprises four main aspects that reflect the structure of the resulting digital twin. The first is the design of decision support systems adapted for the specific production network configuration tasks. The second is a common base architecture providing consolidated data and additional functions to the applications. The third is a data acquisition scheme to achieve synergies. The fourth part is an implementation process allowing organisations to organically develop their digital twin while maximising its utility.

The framework is applied and tested with a large automotive supplier to support several decisions in its production network, demonstrating the approach's utility.

The results show that this design approach to digital twins of production networks allows organisations to quickly manifest lasting solutions to improve their network configuration and continuously build upon them. Researchers may use the platform this work provides to design production network decision support systematically. The competitive advantages companies can realise with such systems are considerable, and widespread adoption could increase value creation efficiency.

Ultimately, this work is a step towards better, more efficient decision-making in production networks in our ever-changing world.

Kurzfassung

Die Konfiguration von Produktionsnetzwerken ist heute so komplex und volatil wie nie zuvor. Um in dem von Wettbewerb und Disruption geprägten Umfeld die richtigen Entscheidungen zu treffen, braucht es eine Entscheidungsunterstützung für zahlreiche Konfigurationsaufgaben, die Daten aus verschiedenen Quellen zusammenführt. Viele Unternehmen nutzen jedoch weiterhin manuelle Entscheidungsprozesse und fallbezogene Modellierungen, was ihre Entscheidungen verlangsamt und verschlechtert. Wie Unternehmen am besten ein Entscheidungsunterstützungssystem im Sinne eines digitalen Zwillings ihres Produktionsnetzwerks schaffen können, bleibt eine offene Frage.

Diese Arbeit hat zum Ziel, Unternehmen einen Weg zu einem solchen System aufzuzeigen. Sie geht daher der Frage nach: *Wie lassen sich Entscheidungsunterstützungssysteme für die Konfiguration globaler Produktionsnetzwerke realisieren, Entscheidungsaufwände verringern und schnellere und bessere Entscheidungen ermöglichen?*

Um diese Frage zu beantworten, wird eine Forschungsmethodik der Design Science angewendet, die sich auf den pragmatischen Nutzen des Artefakts konzentriert.

Das entwickelte Rahmenwerk für den Entwurf globaler Produktionsnetzwerk-Zwillinge umfasst vier Aspekte: Ein Entwicklungsvorgehen für an Konfigurationsaufgaben angepasste Entscheidungsunterstützungssysteme, eine gemeinsame Basisarchitektur, die den Anwendungen Daten und zusätzliche Funktionen bereitstellt, ein gemeinsames Datenerfassungsschema und ein Implementierungsprozess, zur organischen, nutzenorientierten Entwicklung des unternehmensspezifischen digitalen Zwillings.

Das Rahmenwerk wird bei einem großen Automobilzulieferer angewendet und getestet, um mehrere Entscheidungen in dessen Produktionsnetzwerk zu unterstützen, wodurch der Nutzen des Ansatzes demonstriert wird.

Dieser Entwicklungsansatz für digitale Zwillinge von Produktionsnetzwerken ermöglicht es Unternehmen, schnell dauerhafte Lösungen zur Netzwerkkonfiguration zu finden und diese kontinuierlich weiterzuentwickeln. Die Ergebnisse können von Forschenden genutzt werden, um systematisch Entscheidungshilfen für Produktionsnetzwerke zu entwickeln. Die Wettbewerbsvorteile, die Unternehmen mit solchen Systemen erzielen können, sind beträchtlich.

Diese Arbeit ist ein Schritt hin zu einer besseren und effizienteren Entscheidungsfindung in Produktionsnetzwerken in einer sich ständig verändernden Welt.

Contents

Abbreviations

Abbreviation	Description
&	and
€	Euro
a	Year (Latin: annum)
AAS	Asset Administration Shell
ABS	Agent-Based Simulation
AC	Analytical Capability
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANP	Analytic Network Process
API	Application Programming Interface
APS	Advanced Planning System
APVA	Automated Planned Volume Allocation
AR	Accuracy Requirements
ARIMA	Autoregressive Integrated Moving Average
AT	Application Type
AtO	Assemble-To-Order
BPMN	Business Process Model and Notation
BR	Behavioural Requirement
c.f.	compare from
CAD	Computer Aided Design
CAQ	Computer Aided Quality
CBI	Capacity-Based Initiation
CIMM	Core Information Model Manufacturing
cmp.	Compare
CMSD	Core Manufacturing Simulation Data
CO_2	Carbon Dioxide

Abbreviation	Description
CPS	Cyber Physical Systems
CRM	Customer Relationship Management (System)
CSV	Comma Separated Values
d	Day
DB	Database
DCF	Discounted Cash Flow
DD	Data Demand
DES	Discrete Event Simulation
DIN	German Institute for Standardisation (Deutsches Institut für Normung e. V.)
DM	Data Model
DMC	Decision Making Committee
DoE	Design of Experiments
CR	Computational Restriction
DR	Data Restriction
DS	Digital Shadow
DSRM	Design Science Research Methodology
DSS	Decision Support System
DT	Digital Twin
e.g.	for example (Latin: exempli gratia)
ELECTRE	ÉLimination Et Choix Traduisant la REalité (French: Elimination and Choice Translating Reality)
EMO	Evolutionary Multi-Objective Optimisation
ER	Entity Relationship (Model)
ERP	Enterprise Resource Planning (System)
ES	Expert System
ESG	Environmental, Social, Governmental
et al.	and others (Latin: et altera)
etc.	and so forth (Latin: et cetera)

Abbreviation	Description
EtO	Engineer-To-Order
FTE	Full Time Equivalent (Personnel Measurement)
GA	Genetic Algorithm
GPN	Global Production Network
HR	Human Resources (Department)
i.e.	that means (Latin: id est)
II	Implementation Item
ILP	Integer Linear Programming
IP	Intellectual Property
IPN	International Production Network
IT	Information Technology
JSON	JavaScript Object Notation
KDD	Knowledge Discovery in Databases
KPI	Key Performance Indicator
LP	Linear Programming
LTPA	Long Term Planning Assistant
LTP-M	Long Term Planning and Site Strategy Manufacturing
m	Month
MADM	Mult-Attribute Decision Making
MARS	Multivariate Adaptive Regression Splines
MCDM	Multi-Criteria Decision Making
MCS	Monte Carlo Simulation
MES	Manufacturing Execution System
MI	Manual Initiation
MILP	Mixed-Integer Linear Programming
ML	Machine Learning
MODM	Multi-Objective Decision Making

Abbreviation	Description
MR	Model Restriction
MSS	Management Support Systems
MtO	Make-To-Order
MtS	Make-To-Stock
NASA	National Aeronautics and Space Administration
NN	Neural Network
NPC	Net Present Costs
NPV	Net Present Value
ODSS	Organisational Decision Support Systems
OEE	Overall Equipment Efficiency
OEM	Original Equipment Manufacturer
OR	Operations Research
PCA	Principle Component Analysis
PDF	Probability Density Function
PLM	Product Lifecycle Management
PN	Production Network
PNC	Production Network Configuration
POA	Post-Optimality Analysis
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
PRQ	Partial Research Question
PSI	Publish-Subscribe Initiation
PSO	Particle Swarm Optimisation
PVA	Planned Volume Allocation
R&D	Research and Development
RQ	Research Question
RRI	Request-Response Initiation
SA	Simulated Annealing

Abbreviation	Description
SBU	Strategic Business Unit
SC	Supply Chain
SCDT	Supply Chain Digital Twin
SCOR	Supply-Chain-Operations-Reference (Model)
SD	System Dynamics
SFD	Space-Filling-Designs
SoS	System of Systems
SQL	Structured Query Language
SysML	Systems Modelling Language
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TS	Tabu Search
UML	Unified Modelling Language
VDI	Association of German Engineers
VUCA	Volatility, Uncertainty, Complexity, Ambiguity
XML	Extensible Markup Language

Symbols

Symbol	Description	Unit
$\emptyset$	Empty set	
$\Rrightarrow$	Hierarchically superior	
$\rightleftharpoons$	Interlocked	
$\rightharpoondown$	Semi-locked	
$\Rightarrow$	Dependent	
$\rightarrow$	Semi-dependent	
$\nRightarrow$	Independent	
$\Leftrightarrow$	Conflicting	
$\looparrowleft$	Semi-conflicting	
$\rightleftarrows$	Complimenting	
$\nLeftrightarrow$	Non-conflicting	
$\rightsquigarrow$	Refining	
$\curvearrowright$	Rendering	
$\twoheadrightarrow$	Optimising	
$\leadsto$	Reevaluating	
$\mathbb{R}^+$	Positive real numbers	
$\hat{\delta}$	Change type	
$\widehat{\Delta}^{(STATE)}$	Set of state change types	
ϵ	Environment	
ϵ_s	Environment of production system s	
$\epsilon_s^{(IND)}$	Independent part of the environment of production system s	
Φ_m	Space of feasible Solutions of model m	
$\Phi_{m_1,m_2}^{(CONF)}$	Conflicted feasible decision space between model m_1 and m_2	
$\Phi_{m_1,m_2}^{(LOCK)}$	Locked feasible decision space between model m_1 and m_2	
γ	Adaption option	
$\gamma_{\hat{\gamma}}$	Adaption option for choice $\hat{\gamma}$	

Symbol	Description	Unit
$\hat{\gamma}$	Adaption choice	
$\Gamma_{\hat{\gamma}}$	Set of adaption options in adaption choice $\hat{\gamma}$	
$\hat{\Gamma}_m$	Set of adaption choices for model m	
$\hat{\Gamma}^{(DEL)}$	Set of delimitation adaption choices	
$\kappa_{\omega}^{(SC)}$	Assumed occurrence likelihood of scenario ω	
$\iota^{(CRI)}$	Criteria weight norm	
$\iota^{(DD)}$	Data demand weight norm	
$\iota^{(DYN)}$	Dynamic weighing of utility	
$\iota^{(SC)}$	State change weighing index	
$\kappa_{\omega}^{(SC)}$	Assumed occurrence likelihood of scenario ω	
λ	General implementation item	
$\lambda_p^{(BMA,CAL)}$	Calibration service for parameter p	
$\lambda_d^{(DAS)}$	Data acquisition strategy for data demand d	
$\Lambda^{(IS)}$	Set of implementation items comprising an implementation strategy	
$\vec{\Lambda}^{(IS)}$	Set of ordered implementation strategies comprising an implementation roadmap	
$\mu_{\sigma}^{(OWN)}$	Owner of scenario space σ	
π	Decision process	
Π	Set of decision processes	
σ	Scenario space	
Σ	Set of scenario spaces	
$\Sigma_{\omega}^{(REF)}$	Reference scenario space set of scenario ω	
Υ	Information set	
ξ	User role	
Ξ_{μ}	Set of user roles associated with user μ	
ζ	Risk preference angle	
$\zeta_{\vec{\Lambda}^{(IS)}}^{(LOB)}$	Lower bound of risk preference range of implementation roadmap $\vec{\Lambda}^{(IS)}$	

Symbol	Description	Unit
$\zeta_{\vec{\Lambda}^{(IS)}}^{(UPB)}$	Upper bound of risk preference range of implementation roadmap $\vec{\Lambda}^{(IS)}$	
$\eta_j^{(SVEI)}$	Spatial variance of influence j	
$\eta_j^{(TVEI)}$	Temporal variance of influence j	
θ	Time	
θ_0	Start time	
$\Delta\theta^{(LT,PROD)}$	Production lead time	
$\Delta\theta^{(PER)}$	Period length	
$\Delta\theta_{\Lambda^{(IS)}}^{(REAL)}$	Estimated realisation time for implementation strategy $\Lambda^{(IS)}$	
$\Delta\theta^{(REAL,REF)}$	Reference realisation time	
$\Delta\theta^{(TH)}$	Duration of time horizon	
ψ	Transition	
Ψ	Set of transitions	
Ψ_ψ	Set of transitions in transition ψ	
$\Omega_{\epsilon_s^{(IND)}}$	Set of scenarios for the independent environment $\epsilon_s^{(IND)}$	
$\Omega_\sigma^{(ALT)}$	Set of alternative scenarios in scenario space σ	
$\Omega_\sigma^{(OTH)}$	Set of other scenarios in scenario space σ	
$\Omega_\omega^{(REF)}$	Reference scenario set for scenario ω	
ω	Scenario	
$\omega_\sigma^{(NOM)}$	Nominal scenario in scenario space σ	
$\omega^{(OBS)}$	Obsolete scenario	
$\omega_\omega^{(PAR)}$	Parent scenario of scenario ω	
a	Application	
$B_a^{(BT)}$	Benefits of an enhancing dependency of an application a	
$C_{\lambda_d^{(DAS)}}$	Costs of data acquisition strategy $\lambda_d^{(DAS)}$	€
$C_{\lambda_d^{(DAS)}}^{(SU)}$	Set up costs of data acquisition strategy $\lambda_d^{(DAS)}$	€
$c_{\lambda_d^{(DAS)}}^{(FO)}$	Fixed operating costs of data acquisition strategy $\lambda_d^{(DAS)}$	€/d
$c_{\lambda_d^{(DAS)}}^{(VO)}$	Variable operating costs of data acquisition strategy $\lambda_d^{(DAS)}$	€/[use]

Symbol	Description	Unit
d	Data demand	
D_a	Set of data demands for application a	
D_m	Set of data demands for model m	
e	Element	
$e^{(REP)}_{e,f^{(INT)}_{\hat{e}_1,\hat{e}_2}}$	Replacement element for element e with respect to interaction function $f^{(INT)}_{\hat{e}_1,\hat{e}_2}$	
ê	Element type	
$\hat{e}^{(FOCAL)}_{\hat{\gamma}}$	Focal element type of abstraction adaption choice $\hat{\gamma}$	
$\hat{e}^{(SEL)}_{\hat{\gamma}}$	Selection element type of delimitation adaption choice $\hat{\gamma}$	
E	Set of elements	
$E^{(FOCAL)}_{m}$	Focal elements in model m	
$E^{(FOCAL)}_{\gamma,m}$	Focal elements in model m determined by adaption option γ	
$E^{(IS)}_{\hat{e}_2,e,f^{(INT)}_{\hat{e}_1,\hat{e}_2}}$	Set of in-scope elements of type $\hat{e}_2$ interacting through $f^{(INT)}_{\hat{e}_1,\hat{e}_2}$ with element e of type $\hat{e}_1$	
$E^{(OOS)}_{\hat{e}_2,e,f^{(INT)}_{\hat{e}_1,\hat{e}_2}}$	Set of out-of-scope elements of type $\hat{e}_2$ interacting through $f^{(INT)}_{\hat{e}_1,\hat{e}_2}$ with element e of type $\hat{e}_1$	
$E^{(SEL)}_{\hat{e}^{(SEL)}_{\hat{\gamma}},\gamma}$	Set of selected elements of selection element type $\hat{e}^{(SEL)}_{\hat{\gamma}}$ in adaption option γ	
$\hat{E}_m$	Set of element types in model m	
$\hat{E}^{(DES)}$	Set of new element types desired	
$\hat{E}^{(IMP)}$	Set of element types to be implemented	
$\hat{E}^{(REL)}$	Set of relational element types	
$\hat{E}^{(ABS)}_{\hat{\gamma}}$	Set of element types affected by adaption choice $\hat{\gamma}$	
$f^{(ABS)}_{\gamma}$	Abstraction function for adaption option γ	
$f^{(ABS)}_{h}$	Abstraction function for property h	
$f^{(CAL,DET)}$	Deterministic calibration function	
$f^{(CAL,REG)}$	Regressive calibration function	
$f^{(INT)}_{\hat{e}_1,\hat{e}_2}$	Interaction function between two element types $\hat{e}_1$ and $\hat{e}_2$	
$f^{(REP)}_{f^{(INT)}_{\hat{e}_1,\hat{e}_2},\hat{e}_2}$	Replacement function for elements of type e_2 with respect to the interaction $f^{(INT)}_{\hat{e}_1,\hat{e}_2}$	

Symbol	Description	Unit
$f_j^{(IT)}$	Influence function of influence j	
$\boldsymbol{f}_m$	Vector function of model m	
$\boldsymbol{f}_s$	Vector function describing the behaviour of the system s	
g	objective	
G	Set of objectives	
$G^{(CON)}$	Set of constraint objectives	
$G^{(DC)}$	Set of decision criterion objectives	
$G_d^{(DD)}$	Set of data demand criteria associated with data demand d	
$G_\pi^{(DP)}$	Set of objectives used in decision process π	
$G^{(OPT)}$	Set of optional decision objectives	
h	Property	
$\hat{h}$	Property type	
$\widehat{\mathrm{H}}_\gamma^{(ADP)}$	Set of property types after application of an adaption option γ	
$\widehat{\mathrm{H}}_{\hat{\gamma}}^{(ORG)}$	Set of original property types affected by adaption choice $\hat{\gamma}$	
$\widehat{\mathrm{H}}_{\hat{e}}$	Property type set of element type $\hat{e}$	
i	Index	
$I_L^{(IO)}$	Index set of input-output tuples of set L	
j	Influence	
$J^{(DS)}$	Set of decision situation influences	
$J^{(EI)}$	Set of external influences	
k	Capability	
K	Set of capabilities	
K_ψ	Set of capabilities required for transition ψ	
K_q	Set of capabilities required for capacity q	
K_r	Set of capabilities required of resource r	
L	Set of input-output tuples	
l	Input-output tuple	

Symbol	Description	Unit
m	Model	
m_{σ}	Model used to define scenario space σ	
$m^{(APVA)}$	APVA model	
$m^{(LTPA)}$	LTPA model	
$m^{(NEW)}$	Revised version of model m	
M_{π}	Set of models used in decision making process π	
$N^{(AII)}$	Number of available implementation items	
$N_{L}^{(CAL)}$	Number of tuples in L	
$N^{(DO)}$	Number of development options	
$N^{(EXP)}$	Number of experiments	
$N^{(MII)}$	Maximum number of implementation items per development options	
$N_{\lambda_d^{(DAS)}}^{(SYNC)}$	Number of synchronisations using data acquisition strategy $\lambda_d^{(DAS)}$	
$N^{(MOD)}$	Number of models	
O	Set of outputs	
O_{ψ}	Set of outputs used in transition ψ	
O_{Ψ}	Set of outputs used in the set of transitions Ψ	
O_{l}	Set of outputs in tuple l	
p	Parameter	
$\boldsymbol{p}_{m}$	Internal parameter vector of model m	
P_{π}	Set of parameters used in decision process π	
q	Capacity	
q_{r}	Capacity of resource r	
$q_{\hat{r}}^{(AIC)}$	Available implementation capacity of type $\hat{r}$	
$q_{\hat{r},\Lambda^{(IS)}}^{(ICD)}$	Implementation capacity demand of type $\hat{r}$ for implementation strategy $\Lambda^{(IS)}$	
$\boldsymbol{q}_{t}^{(DEM)}$	Capacity demand vector in period t	
$\boldsymbol{q}_{s,t}$	Capacity vector for production system s in period t	

Symbol	Description	Unit
Q	Set of capacities	
Q_{ψ}	Set of capacities used in transition ψ	
Q_r	Set of capacities of resource r	
Q_s	Set of capacities of production system s	
r	Resource	
$r_R^{(ABS)}$	Abstracted replacement resource for set or resources R	
$\hat{r}$	Capacity type	
R	Set of resources	
R_s	Set of resources in production system s	
$\hat{R}^{(IR)}$	Set of implementation capacity types	
s	(Production) system	
t	Period	
$t_{\omega}^{(DIV)}$	Division period of scenario ω	
$t_{\omega}^{(PLAN)}$	Planning period of scenario ω	
T	Set of periods	
U	Set of inputs	
U_{ψ}	Set of inputs used in transition ψ	
U_{Ψ}	Set of inputs used in the set of transitions Ψ	
U_l	Set of inputs in tuple l	
$v_g^{(DD)}$	Fulfilment of data demand criterion g	
$v_g^{(DD,RL)}$	Requirement level for data demand criterion g	
$v_g^{(DD,SL)}$	Satisfaction level for data demand criterion g	
$v_{j_1,j_2}^{(IC)}$	Comparison value between influences j_1 and j_2	
$v_p^{(INF)}$	Influence strength of parameter p	
$v_{\pi,j}^{(IV)}$	Influence value of influence j in decision process π	
$v_p^{(OPP)}$	Calibration opportunity of parameter p	
$v_p^{(UNC)}$	Uncertainty associated with parameter p	

Symbol	Description	Unit
$\tilde{v}_g^{(DD)}$	Evaluation fulfilment of data demand criterion g	
$V_p^{(CAL)}$	Calibration priority of parameter p	
$V_{\Lambda^{(IS)}}^{(DYN)}$	Dynamic utility of implementation strategy $\Lambda^{(IS)}$	
$V_{\Lambda^{(IS)}}^{(STAT)}$	Static utility of implementation strategy $\Lambda^{(IS)}$	
$\dot{V}_{\Lambda^{(IS)}}^{(DYN)}$	Dynamic utility rate of implementation strategy $\Lambda^{(IS)}$	
$\dot{V}_{\Lambda^{(IS)}}^{(DYN,OPT)}$	Optimistic dynamic utility rate of implementation strategy $\Lambda^{(IS)}$	
$\dot{V}_{\Lambda^{(IS)}}^{(DYN,PES)}$	Pessimistic dynamic utility rate of implementation strategy $\Lambda^{(IS)}$	
$w_j^{(ACDS)}$	Weight of influence j in deduction of desired analytical capability	
$w_{j,\pi}^{(EXIN)}$	Relevance of an influence j on a decision process π	
$w_d^{(BEN)}$	Benefit weight of data demand d	
$w_{g^{(DD)}}^{(DDB)}$	Weight of data demand criterion $g^{(DD)}$	
$w_{g,\pi}^{(OBJ)}$	Weight of an objective g in a process π	
$w_{g,j}^{(OIEI)}$	Impact influence j has on objective g	
$w_{\hat{\delta}}^{(SCT)}$	Weight of change type $\hat{\delta}$ in state change index	
$W_\pi^{(AC)}$	Desirability of high analytical capability in decision process π	
x	Input parameter / Decision variable	
$\boldsymbol{x}$	Input parameter vector / Decision strategy	
$\boldsymbol{x}_s$	Decision strategy vector for system s	
$x_s^{(ALO)}$	Allocation for system s	
$\boldsymbol{x}_{s,t}^{(ALO)}$	Allocation strategy for system s in period t	
$x_s^{(CON)}$	Configuration for system s	
$\boldsymbol{x}_{s,t}^{(CON)}$	Configuration strategy for system s in period t	
X_m	Set of decision variables of model m	
X_π	Set of decision variables in decision process π	
$X_m^{(FIX)}$	Set of fixed decision variables in model m	
$X_\pi^{(FIX)}$	Set of fixed decision variables in decision process π	

Symbol	Description	Unit
$X_m^{(INC)}$	Set of inconsequential decision variables in model m	
$X_\pi^{(INC)}$	Set of inconsequential decision variables in decision process π	
$X_m^{(INC,PDC)}$	Set of predictively defined inconsequential decision variables in model m	
$X_m^{(INC,PSC)}$	Set of prescriptively defined inconsequential decision variables in model m	
$X_s^{(IP)}$	Input parameter space of system s	
$X_m^{(PDC)}$	Set of predictively defined decision variables in model m	
$X_m^{(PSC)}$	Set of prescriptively defined decision variables in model m	
$X_m^{(SUB)}$	Set of subject decision variables in model m	
$X_\pi^{(SUB)}$	Set of subject decision variables in decision process π	
$X_m^{(SUB,PDC)}$	Set of predictively defined subject decision variables in model m	
$X_m^{(SUB,PSC)}$	Set of prescriptively defined subject decision variables in model m	
y_t	State at period t	
$\boldsymbol{y}_{s,t}$	State vector for system s in period t	
$y_{t,\omega}^{(PLAN)}$	Planned state in scenario ω in period t	
$y_{t,\omega}^{(PLAN,FRO)}$	Frozen planning state in scenario ω in period t	
$y_\sigma^{(START)}$	Starting state of scenario space σ	
$\Delta y_{t_1 \rightarrow t_2}^{(STATE)}$	Absolute state change index from time t_1 to t_2	
$\Delta y_{t_1 \rightarrow t_2,\hat{\delta}}^{(STATE)}$	State change in change type $\hat{\delta}$ from time t_1 to t_2	
$\overline{\Delta y}^{(STATE)}$	Absolute state change threshold	
$\boldsymbol{z}$	Response vector	
$\boldsymbol{z}_{\boldsymbol{x}_s}$	Consequence vector for decision strategy $\boldsymbol{x}_s$	
$\mathbb{E}[x]$	Expected value of variable x	
$\epsilon[x]$	Prediction accuracy with regard to variable x	
$\varsigma[x]$	Standard deviation of variable x	
$\bar{\varsigma}[x]$	Average standard deviation of variable x	

1 Introduction

Global Production Networks (GPN) are complex systems of multiple interacting sites with differing technological and organisational capabilities and processing capacities that must continuously adapt to the requirements of their organisations and environments (Lanza, & Ferdows et al., 2019, 824ff). While decreasing trade barriers, lower costs of shipments and international consolidation have brought about today's networks (F. Jacob & Strube, 2008, p. 6), they now face a world in which those trends have stopped, if not reversed (Gilbert, & Lang et al., 2023; Gunnella & Quaglietti, 2019). At the same time, increasing trade barriers seem not to lead to more stability but, if anything, more *volatility* (Christopher & Holweg, 2017, pp. 2–3; The World Bank, 2023). Production networks, however, are fundamentally sluggish and configurational adaptations need time and large investments (Govindan, & Fattahi et al., 2017, p. 109). Thus, companies must make adaptation decisions while facing uncertainty regarding future developments. Herein, production network configuration (PNC) refers to the process and result of alterations to the physical realisation of the network (Friedli, & Mundt et al., 2014, p. 46). These alterations span from introducing different tools at local sites to selecting and setting up new production sites. Depending on an organisation's structure, size and culture, the available configurative levers are wielded by different management levels in various processes and planning projects. Throughout these decisions, several company-specific, strategic goals need to be considered, like cost minimisation, delivery time reduction, quality fulfilment, risk avoidance and mitigation, and the reduction of environmental impacts (Melo, & Nickel et al., 2009).

1.1 Motivation & Problem Statement

To predict the consequences of changes and find the best course of action for PNC problems, mathematical models chiefly originating from Operations Research (OR) can be used. The OR community has developed many approaches throughout the last decades, aided by rapidly evolving computational capabilities. Nevertheless, even though such models can help manage the *complexity* inherent to many configurative decisions, aid in *uncertain* situations and resolve the *ambiguity* of managerial trade-offs, they have yet to see extensive adoption.

Model-based decision-making has developed considerably in other domains in recent years. A decisive factor in this development is the continuous realignment of the models through automatic data transfer from the modelled real system. This concept, coined Digital Twin (DT), allows models to be used at any time in current decision-making situations. Examples of the application of DTs are found across engineering design, quality control, and production system control. DTs are a promising solution even in the production network and supply chain control, principally concerned with scheduling and organising orders throughout the supply chain (Ivanov & Dolgui, 2021).

Thus, this work investigates the viability of DTs for decision support in PNC. The realisation of automatically synchronised model-based decision support systems (DSS) should enable decision-makers to face uncertainty, complexity, and ambiguity found in production networks, using the results of decades of development in the OR community. Synchronisation with the real production network helps address the first-dimension characterising today's much-discussed VUCA world: volatility. Researchers and practitioners utilising OR models agree that a majority of the time in model-based decision-making is spent on data collection, search, preparation, and integration (Costa & Melo, 2022, pp. 15–17; Hochdörffer, & Klenk et al., 2022, p. 2183; Ziegler, & Seifried et al., 2019, p. 224). By reducing or eliminating the necessary time and effort for this, model-based decisions could be made faster and more frequently, supporting the resilience of the employing organisations (Benfer, & Verhaelen et al., 2021, pp. 503–504).

By contrasting PNC tasks with other DT applications, the challenges associated with DTs of GPNs become apparent. DTs in many existing applications are used frequently, which offsets the necessary investments to develop and deploy them. Conversely, PNC decisions are relatively infrequent (Kiesel, & Gützlaff et al., 2024, p. 337). Whereas many DTs are focused on particular tasks, a DT of GPNs should support multiple decision types to reduce the necessary investment burden. Hence, an approach that adequately supports multiple different decision tasks while realising synergies between them is required. Another challenge lies in data and organisational integration. Whereas DTs of smaller systems can rely on very few data sources, DTs of GPN need to integrate several distinct data sources, which need to be acquired, prepared and integrated. Finally, if a DT of a GPN is supposed to address several different tasks, it needs to be integrated within organisational processes and provide decision-makers with as many benefits as possible at low costs.

1.2 Research Objective

The above descriptions show the opportunity and need for improved decision support in production network configuration (PNC). This work shall address this problem by developing a new approach to decision support system (DSS) design that exploits the opportunities afforded by increasing data availability while addressing the specific challenges in PNC. This approach, therefore, needs to address the diversity of configurational tasks, providing individually suitable methodologies. It should also facilitate the realisation of synergies between decision support in multiple tasks and be dynamically expandable. Furthermore, the solution shall streamline data acquisition to reduce the time and effort spent to realise the decision support. Finally, the solution needs to be mouldable to the particular requirements of the employing organisation, ensuring a positive contribution to its performance.

1.3 Research Approach

This work documents the epistemological process for addressing the previously described research objective, characterised by an epistemological perspective on a problem and a methodological approach to the discovery process. The epistemological perspective is a prescientific value-based belief system which defies any test of ultimate truth (Guba & Lincoln, 1994, p. 107). The methodological approach describes the procedure by which knowledge of the subject matter is obtained.

Scientific work can be partitioned into formal sciences, which intend to create logically consistent systems of symbols and rules for their application, and empirical sciences, which describe, explain, and form empirically observable parts of reality. Statements of empirical sciences must satisfy both logical consistency and factual evidence. Formal and empirical sciences are divided into foundational sciences, focusing on improving theory for explaining and predicting natural or other phenomena, and applied sciences, which seek practical goals by applying existing scientific knowledge (Cohen, 2021, p. 28). This work assumes an applied science perspective and is thus primarily concerned with a design question, as H. A. Simon (1996, p. xii) stipulated.

A generally accepted central paradigm is considered foundational to scientific progress (Kuhn, 1996, p. 25). This work adopts the design science research paradigm, first conceptualised by H. A. Simon (1996). Design science is rooted in pragmatism and focuses on creating innovative artefacts that solve real-world problems (Hevner & Chatterjee, 2010, p. 9). According to Goldkuhl (2012, p. 93), the epistemological foundations of pragmatism underlying design science research are (i) a focus on utility, usefulness and contribution to practice, (ii) knowledge development through building and intervention, (iii) problematic situations as a starting and driving point for inquiry and design, (iv) the search for what is possible and desirable, (v) going beyond description; aiming for prospective, normative, and prescriptive knowledge.

As this work's objective is of a pragmatic nature, it adopts the design science research methodology (DSRM) proposed by Peffers et al. (2007) as its methodological process. It consists of six activities, nominally portrayed in sequential order, though almost any starting point is conceivable (Peffers, & Tuunanen et al., 2007, pp. 52–56):

(1) *Problem identification and motivation* describe the definition of a specific research problem and the expected value and importance of a solution. This activity can involve the "conceptual atomisation" of the problem to grasp its complexity.
(2) *Defining the objectives for a solution* calls for the specification of what a solution should provide to satisfy the problem under explicit consideration of what is possible and feasible. The developed solution should be better than exciting solutions or solve problems yet to be addressed.
(3) *Design and Development* means the creation of the artefact that embeds the research contribution.
(4) *Demonstration* uses the artefact to solve one or more problem instances.
(5) *Evaluation* describes the critical reflection of the artefact's performance through observation and measurement, comparing the objectives to the actual results. After this activity, the artefact may be iterated in another instance of (3), or the researchers may continue with (6), depending on the circumstances and the level of satisfaction with the results achieved.
(6) *Communication* refers to publishing the problem, its importance, the artefact, its utility, novelty, and design rigour.

1.4 Structure

The remainder of this work is structured in eight chapters that mirror the DSRM, as shown in Figure 1-1. The first chapter explores the motivation and practical relevance of the problem for globally operating companies. Furthermore, the research methodological design of this work is outlined. The second chapter discusses the research fundamentals necessary to grasp the solution space for the problem specified above and the methods necessary to design and develop an artefact to solve the problem. Specifically, Chapter 2 describes extant knowledge on (i) production network configuration (PNC), (ii) decision support, (iii) data, information, and information systems in production, and (iv) digital twins (DT). After that, Chapter 3 defines the objectives of the artefact and critically examines existing approaches. A reflection on the extant research deficit emerges from this examination, resulting in a central research question and four complementary partial research questions that focus and structure the research efforts. Chapter 4 describes the artefact's conceptual development and outlines the theoretical foundations of the solution design. It then transforms the concept into a detailed design model structured into the aspects (i) decision support system (DSS) design, (ii) DT architecture, (iii) data acquisition, and (iv) organisational integration. It develops answers to the postulated research questions through each and in conjunction with them[1]. The demonstration of the artefact in a prototype and an industrial use case is described in Chapter 5. Chapter 6 critically reflects on and discusses the results of this demonstration, measuring the quality of the solution in relation to the objectives defined in Chapter 3. Finally, the work closes with a summary in Chapter 7.

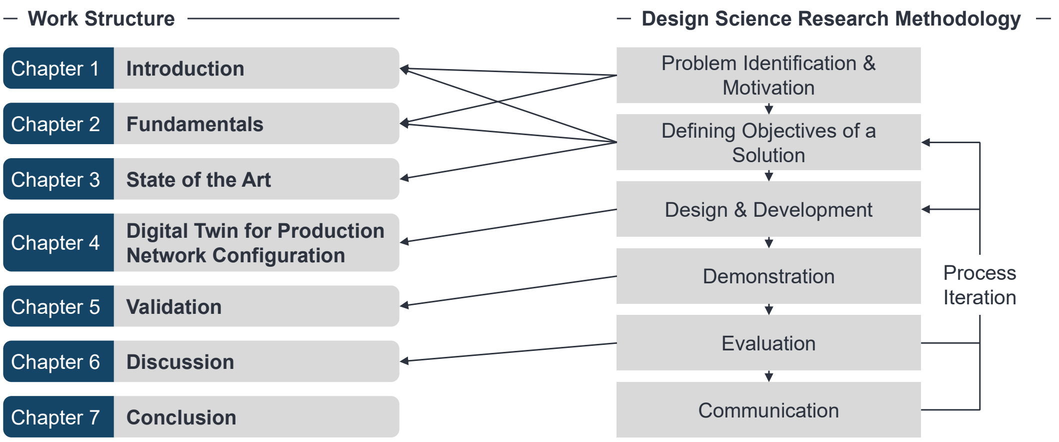

Figure 1-1: Structure of this Work and Relation to the Design Science Research Methodology According to Peffers et al. (2007)

[1] The process iterations undertaken to refine the artefact are not discussed explicitly in the text except for noteworthy cases. In general, the artefact is iterated based on several partial use cases, only the last of which are discussed to keep the present work succinct.

2 Fundamentals

This chapter explores the relevant fundamentals regarding the configuration of production networks in 2.1, decisions and decision support in 2.2, data and information systems in 2.3, and finally digital twins in 2.4. It serves to specify the previously practically motivated problem, to contextualise the framework developed in the following chapters, and to explain the basic methods employed.

2.1 Production Network Configuration

The configuration of production networks is the central task this work addresses. This section commences with a discussion of industrial organisations, their environment, structure, and business processes in 2.1.1. Then, 2.1.2 offers a brief exploration of production as a concept. The focal system of this work, production networks, is discussed in 2.1.3. Finally, 2.1.4 introduces production management and network configuration, the organisational tasks this work is concerned with.

2.1.1 Industrial Organisations

In the past two centuries, production has been primarily carried out by industrial organisations with differing legal structures. These organisations provide products and services to customers. They pursue the interests of their owners, usually but not exclusively measured in economic value. These organisations form the boundary conditions of this work, which investigates how systems supporting their production-related decisions should be designed and developed.

According to Porter (2004, p. 38), the activities an industrial organisation performs, hereinafter called business processes (BP), can be categorised into *primary activities*, which are directly responsible for creating value in a company, and *support activities* that enable the execution of the primary activities. The activities listed by (Porter, 2004, pp. 36–43) represent the functions of an industrial organisation. Each activity may be replicated multiple times in different value chains inside a company (Porter, 2004, pp. 33–36). Each primary and support activity comprises multiple direct, indirect and quality-assuring sub-activities (Porter, 2004, pp. 43–44). Business processes form a hierarchy, which may be divided into several levels, for example, as described by Rummler and Ramias (2010, pp. 85–87). Variants of Porter's generic value chain structure, which is presented in Figure 2-1 such as the Supply Chain Operations Reference

(SCOR) model (Bolstorff & Rosenbaum, 2012, pp. 10–11), or the St Gallen Management Model (Rüegg-Stürm, 2005, pp. 11–12), complement it and reflect the heterogeneity of real organisational structures.

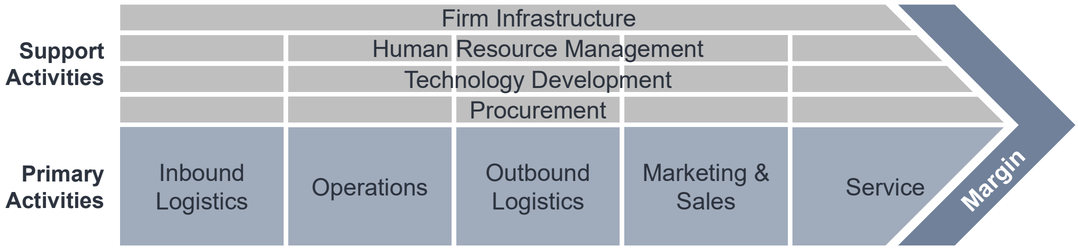

Figure 2-1: Generic Activities in a Value Chain according to Porter (2004, p. 37)

Organisations vary significantly in how they structure processes. The *organisational structure*, i.e., the subdivision of a company into departments, can be aligned with different functions in a functional organisation, with market or product categories in a divisional organisation or with geographical regions in a regional organisation (Rüegg-Stürm, 2005, pp. 36–38). The degree of centralisation may differ depending on the overall organisational culture and each BP (Verhaelen, 2022, pp. 18–20). The complexity of organisational processes also varies, influenced by exogenous and endogenous complexity drivers, which influence decision-making structures (Verhaelen, 2022, pp. 119–123; Wildemann, 1999, pp. 38–42). With complexity, degree of centralisation, and organisational structure, the knowledge and experience of decision-makers in process change (Harmon, 2010, pp. 72–74).

2.1.2 Production

Production is "the process of physically making a product from its material constituents" (Chatti, & Laperrière et al., 2019, p. 1373). This process is comprised of one or more physical processes, divided into assembly, which involves the joining of components without plastic change and fabrication, which involves the physical alteration of materials, components and products (Chatti, & Laperrière et al., 2019, p. 1132). Production processes are value-creating, transforming purchased input factors into higher-value output factors that are in demand (Günther & Tempelmeier, 2012, p. 2). The term manufacturing is often used synonymously with production, but it also includes the necessary non-value-adding processes, such as transportation and storage (Chatti, & Laperrière et al., 2019, p. 1132). Each production process requires the elementary input factors of work, equipment, and materials (Gutenberg, 1971, pp. 2–3). These processes are embedded in a larger value-creation system that includes information flows necessary for planning and control (Schuh & Schmidt, 2014, pp. 3–4).

Such a system, which in the following shall be referred to as a production system, can be viewed from four perspectives (Bundschuh, 2008, p. 21). Schiemenz and Schönert (2005, p. 9) emphasise the *process-oriented* view of a production system that transforms inputs from outside to outputs. Eversheim (1996, p. 1536) describes the infrastructure view, focusing on the resources necessary to transform items in the production system. This *infrastructure view* is commonly used to distinguish different levels of production systems. (i) Machines or stations, (ii) production cells, (iii) production systems, (iv) production segments, (v) production sites, and (vi) production networks may be distinguished in ascending order of granularity (Westkämper, 2008, p. 95; Wiendahl, & ElMaraghy et al., 2007, p. 785). Each of these levels forms a system that includes systems of the previous level and is a subsystem of the subsequent level. The *methodological view*, represented for example by Barth (2005, p. 270), describes a production system as "[…] a methodological ruleset for the configuration of production and all accompanying processes […]". The *integrated view* considers all previously described perspectives jointly, as expressed by Skinner (1985, p. 95 as cited in Bundschuh, 2008, p. 23). Figure 2-2 shows the different views on production and the focus of this work. While this work adopts the integrated view, it primarily considers levels iii-vi of the infrastructure view, focusing on production networks, which are discussed in more detail in the following section.

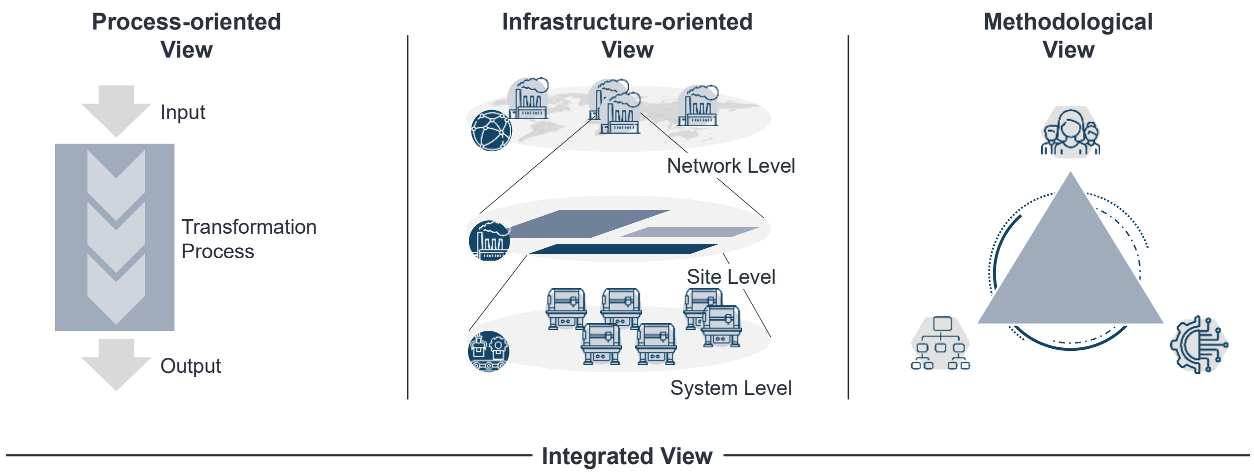

Figure 2-2: Different Views on Production according to Bundschuh (2008, pp. 21)

Production systems may be differentiated by several characteristics related to the production output, the production process or the input factors (Günther & Tempelmeier, 2012, p. 10). Figure 2-3 shows a morphological box of production according to Günther and Tempelmeier (2012, pp. 10–22). For this work, the composition of products, the production program characteristics, the work system arrangement, the type of material flow and its continuity, the number of operation steps, and the resource share are important. This work does not consider the production of immaterial goods, immovable products, divergent, coupled, or regrouping material flows, and localised products.

Output Characteristics	Product Characteristics	Type	Material | Immaterial
		Shape	Unshaped Continuous | Shaped Continuous | Discrete
		Composition	Multi-piece | Single-piece
		Mobility	Movable | Immovable
	Programm Characteristics	Variety	Multi Product | Single Product
		Volume	Mass Production | Variant Production | Series Production | One-off Production
		Market Relation	Engineer to Order | Make to Order | Assemble to Order | Make to Stock
Process Characteristics	Work System Arrangement		Workshop | Serial | Transfer Line | Flow | Flexible Centers | Island
	Structure	Material Flow Shape	Smooth | Convergent | Divergent | Cuppled | Regrouping
		Flow Continuity	Continuous | Batch | Discontinuous
		Product Localisation	Localised | Unbound
		Operation Number	Single Step | Multistep
		Operation Mutability	Fixed Order | Changeable Order
Input Characteristics	Resource Share		Material-intensive | Asset-intensive | Labour-intensive | Information-intensive
	Quality Consistency		Repeatable | Variable

Figure 2-3: Categorisation of Production According to Günther and Tempelmeier (2012, pp. 10–22)

- Whereas *production* is primarily concerned with transforming products, it is only one part of the larger value-creation system. It is closely linked with *logistics*, which provides resources and goods according to the production's and customers' spatial, dispositional, and temporal demands (Fleischmann, 2008, p. 3). Thus, the central functions of logistics are transportation and storage (Fleischmann, 2008, p. 3). Furthermore, the specifications the production process complies with are determined by *product design*. The goods used for production are sourced by *procurement*, which also manages the relation with suppliers. *Sales* acquires customer orders and negotiates prices and delivery times. *Quality management and control* ensure the functionality and safety of the produced products. *Site and resource management* organises, maintains, and provides the infrastructure and equipment at a site. *Human resource management* organises the acquisition, continued training and deployment of employees. *Strategic management* develops and enforces the long-term central decisions of the organisation.

2.1.3 Production Networks & Supply Chains

Production networks (PN), or more specifically global production networks (GPN), "[…] are complex man-made systems […]" constituted by "[…] geographically dispersed production entities, […] interlinked by material, information and financial flows […]." (Lanza, & Ferdows et al., 2019, p. 824). A GPN belongs to one focal company, which can actively shape it (Lanza, & Ferdows et al., 2019, p. 825). In contrast, the related term supply chain (SC) refers to the entities involved in making products spanning organisational boundaries. Furthermore, the SC perspective is derived from logistics management. It primarily focuses on the transport and exchange of information between sites. In contrast, the PN perspective originates from operations management and concentrates on the network's nodes, the production sites (Rudberg & Olhager, 2003, pp. 29–30). GPNs can be characterised by their structure and strategic capabilities.

The structure of a GPN describes the relationships between the sites of the network regarding value streams and different markets. Meyer and Jacob (2008, pp. 164–167) distinguish five phenotypes of production networks: (i) *world factories*, (ii) *value chains*, (iii) *local for local*, (iv) *hub & spoke*, and (v) *web structures*. Friedli et al. (2014, pp. 98–100) further categorise sequential or *convergent value chains* and *hub & spoke* into local and global variants, respectively. Another type of structural categorisation is proposed by Feldmann and Olhager (2019, pp. 169–171), who differentiate production networks by the nature of material flows, which can be *diverging*, i.e., producing many distinct products from few components or *converging*, i.e., using many components to produce few distinct products, *linear*, and *mixed*. These classifications are portrayed in Figure 2-4. Furthermore, the split of production processes across sites describes another characteristic of a GPN. According to Harre (2006, p. 48), three split types can be distinguished: (i) *type splits* describe assignments based on products and components, (ii) *process splits* distribute production steps across sites, and (iii) *volume splits* distribute production volumes.

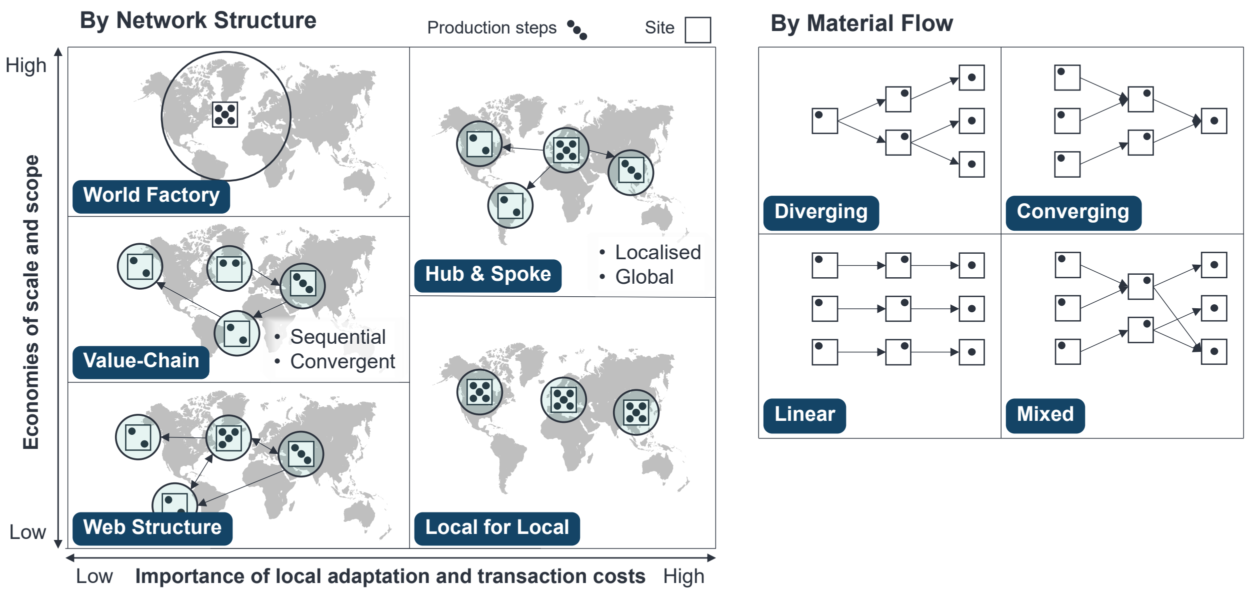

Figure 2-4: Production Network Categorisations

The concept of strategic network capabilities was coined by Shi and Gregory (1998) and describes the overarching long-term abilities that contribute to the organisation's success. These capabilities are (i) *strategic resource accessibility*, (ii) *thriftiness ability*, (iii) *manufacturing mobility*, and (iv) *learning ability* (Shi & Gregory, 1998, pp. 209–210; Wenking, & Dzengelevski et al., 2021, pp. 78–80). The capabilities of different sites constitute these network capabilities. Many other interpretations of site capabilities exist. Größler (2010, p. 652) refers to the classic objectives of production, *cost efficiency*, *quality*, *delivery reliability*, and *flexibility*. Steier et al. (2023, p. 705) define six types of strategic capabilities of sites, representing an update of the network capabilities proposed by Shi and Gregory (1998). Ferdows (1997) describe a related concept, the plant role, of which they identify six. Each type provides different strategic value to the network and requires different competencies, primarily related to the colocation of indirect functions at the plant (S. Simon, & Näher et al., 2008, pp. 354–356). Moreover, the competencies of different sites can relate to specific manufacturing technologies, which require the expertise of the personnel and specific equipment (Liebeck, & Meyer et al., 2008, pp. 195–197). Each site's capabilities are also determined by external factors such as (i) market access, (ii) local costs of labour, energy, material, and capital, (iii) logistics infrastructure, as well as (iv) cultural, (v) legal, and (vi) governmental factors (Lanza, & Ferdows et al., 2019, p. 828).

GPNs can be described as complex systems (Hitomi, 1996, p. 24), shaped by a variety of external and company internal influences. Due to this complexity, they elude a universal understanding from just one perspective, which is reflected in the multitude of organisational functions concerned with aspects of them (Hitomi, 1996, pp. 76–79). Even though GPNs are continuously changing, their shape is seldom ideally suited to the demands placed on them, as their adaption is often slower than the volatile development of influences (Lanza, & Ferdows et al., 2019, p. 836). Following this nature, GPNs are planned and realised on several aggregation levels and time horizons (Váncza, 2016, p. 2). A comprehensive framework of GPN is offered by Lanza et al. (2019, p. 828), as shown in Figure 2-5 , which includes the main tasks in global production: (i) production strategy, (ii) network configuration, and (iii) network management. It also includes the external factors mentioned before, as well as challenges, enablers, and decision support systems. This work focuses on network configuration and decision support systems in particular.

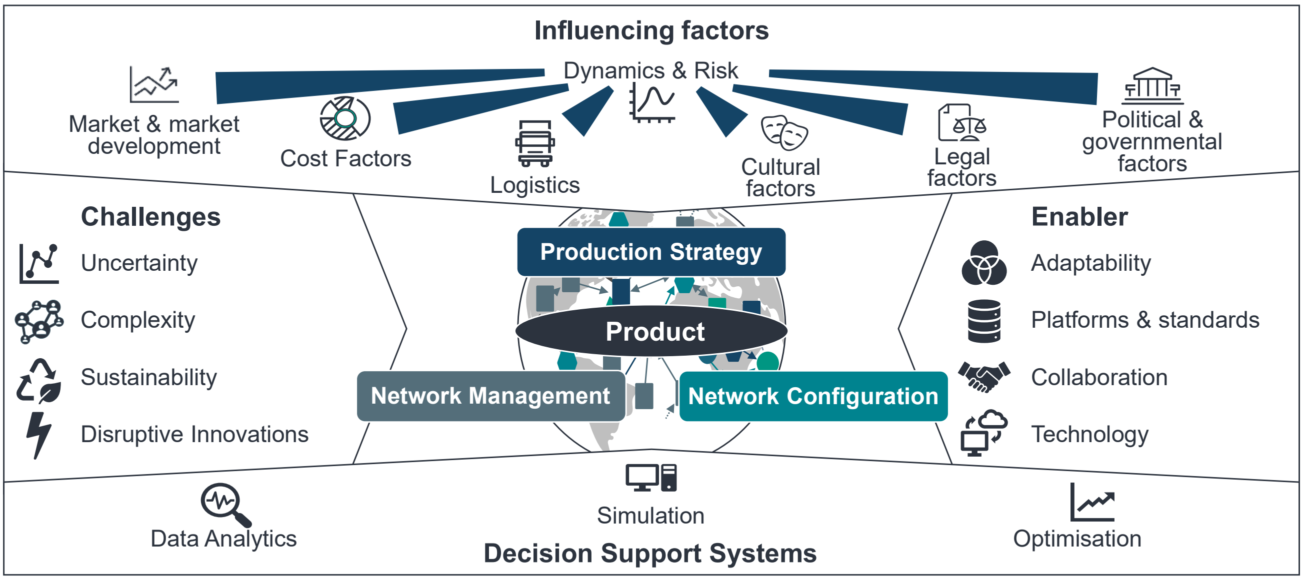

Figure 2-5: Framework of Global Production According to Lanza et al. (2019)

2.1.4 Production Management & Network Configuration

Production management comprises configuration, planning, monitoring and control activities concerned with a production system[2] (Schuh & Schmidt, 2014, p. 1). Using the

[2] In the broad sense.

St. Gallen Management Framework, production management can be structured into normative, strategic, and operative activities (Schuh & Schmidt, 2014, pp. 5–6).

The *(production) network configuration* (PNC) is broadly understood as "[…] the physical design of the individual sites and the network as a whole, ranging from the number of sites and their geographic distribution to the specialisation of sites and their facilities, through to the design of the supply chain." (Friedli, & Mundt et al., 2014, p. 46). Network configuration is sometimes equated with network footprint design (Lanza, & Ferdows et al., 2019, p. 825). PNC refers to both the processes leading to and the resulting physical design of the network. As configuration tasks often overlap with coordination tasks and definitions vary between authors, this work shall subsume all planning activities concerned with the (de-)investment, allocation, and specification of production resources under PNC tasks. These tasks may include allocating transient objects, such as orders, production volumes, or processes, to resources, but are not primarily focused on them.

2.1.4.1 Objectives of Network Configuration

The PNC pursues a set of objectives. These objectives are derived from normative and strategic production management, which defines them as part of the production strategy (Schuh & Schmidt, 2014, pp. 5–6). The objectives are typically motivated by ensuring the company's viability through maximising profits, fulfilling the needs of the different stakeholders, or achieving or securing a market position (Schuh & Schmidt, 2014, p. 5). Objectives can usually be organised in a hierarchy, where sub-objectives contribute to the overarching ones (Klein & Scholl, 2012, p. 93). The company's success objectives encompass *operational objectives*, focused on the efficiency of production, and *market-side objectives* that production can only influence indirectly (Schuh & Schmidt, 2014, pp. 20–21). In addition to these financially oriented objective categories, organisations may also consider *ESG[3] objectives*, essentially describing the interaction of the organisation with its surroundings with a view to long-term sustainability (Souza Barbosa, & Da Silva et al., 2023, p. 3) and *structural and dynamic objectives*, referring to the state and ability of the GPN. Figure 2-6 provides an overview of the five main objective categories for PNC and their typical components.

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[3] ESG stands for environment, social, and governance. Here, environmental mainly refers to the ecological environment. In earlier literature, ESG performance was referred to as corporate social performance (CSP) (Wood, 1991, p. 693).

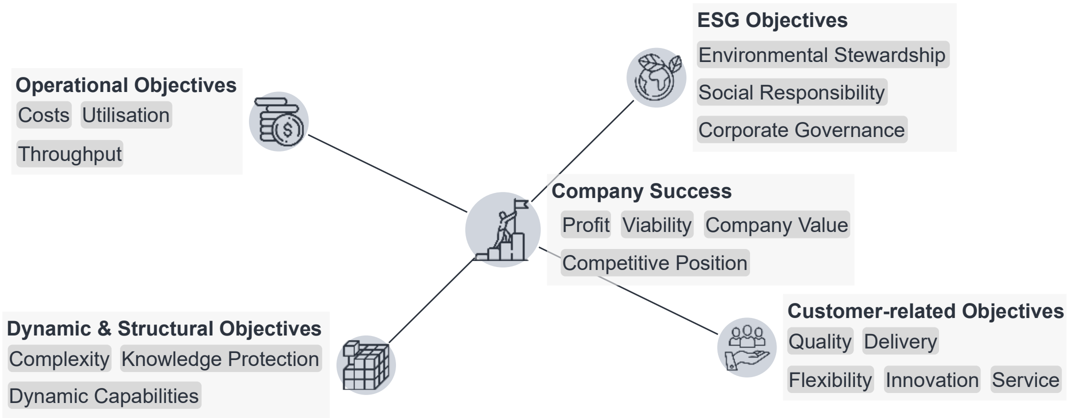

Figure 2-6: Objectives in Production Network Configuration

Operational objectives are primarily concerned with efficiently using the means of production. The most common objective in PNC tasks is cost (Costa & Melo, 2022, p. 8), for example, as total costs of ownership (TCO) or as net present value (NPV). In planning situations where the efficient use of specific resources solely determines the costs, utilisation is also used as an objective.

To influence market-side objectives, companies can use so-called differentiation factors to set themselves apart from the competition and achieve their market-side objectives. According to Thomas (2013, p. 55), those factors are price[4], quality, delivery, flexibility, innovation, and service. Depending on the chosen strategic objectives, these factors may be more or less important. Generally, objectives from an organisational level need to be translated to the level of individual planning processes (Harmon, 2010, pp. 43–44).

ESG performance is measured according to various indices, including several distinct weighted scores for environmental stewardship, social responsibility, and corporate governance (Sandberg, & Alnoor et al., 2023, p. 2475; Souza Barbosa, & Da Silva et al., 2023, p. 2). Several methods can be applied to determine ESG performance (Welsing, 2023, p. 36). ESG objectives have gradually increased in importance over the last few years, particularly concerning greenhouse gas emissions (Costa & Melo, 2022, pp. 8–9).

Structure and dynamic objectives refer to specific aspects of the state of the GPN, like its complexity (Varandani, 2014, p. 38), its intellectual property (IP) protection (Abele,

[4] As the effect production has on prices is included in the operational objectives, it is not included in Figure 2-6.

& Kuske et al., 2011, pp. 60–62), or its dynamic abilities which can be captured as flexibility (Bellmann, & Himpel et al., 2010, p. 222), robustness (Stricker & Lanza, 2014, p. 88), or resilience (Benfer, & Verhaelen et al., 2021, p. 494), and which relate to the performance of other objectives given different realisations of uncertain developments.

2.1.4.2 Production Network Configuration Tasks

Several different terms are used to describe PNC activities depending on the particular circumstances of the examined production system. These activities are often categorised according to the time horizon into operational, tactical, and strategic. However, the time horizons associated with those categories differ significantly. *Network design* or network planning is usually associated with the longest time horizons and decisions regarding the overall structure of the production network and the setup and consolidation of sites (Melo, & Nickel et al., 2009, p. 403). *Site selection* or facility location is tied to network design, focusing on selecting prospective sites (Melo, & Nickel et al., 2009, pp. 402–403). *Technology planning* or choice describes decisions on investments in production technologies regarding productivity and production technology (Jakubovskis, 2017, p. 1095; Lanza & Moser, 2014, p. 398). *Product-mix allocation* describes decisions on selecting the production mix and assigning products or production volumes to sites (Menezes, & Ruiz-Hernandez et al., 2024, p. 1). *Capacity planning* describes the assignment of production volumes to capacities and their change (Briskorn, & Rotfuß et al., 2023, p. 2113). *Investment planning* describes the planning of investments in individual production resources (Bütün, & Kantor et al., 2019, pp. 7–9). *Order allocation* describes the assignment of production orders within the network (Buergin, & Blaettchen et al., 2019, pp. 750–751). These different archetypal PNC Tasks are illustrated in Figure 2-7.

As Figure 2-7 shows, each task is responsible for a set of decisions, which influence the time horizon that has to be considered for the task. The decisions can be either configurative, i.e. deciding on resources for production or allocative, associating different types of resources with each other or production volumes of varying aggregation levels with resources. The time horizon for each task can differ drastically based on the characteristics of the production systems[5]. Furthermore, the processes overlap, and the terms are sometimes used interchangeably[6] (Volling, & Matzke et al., 2013, p. 259).

The planning processes employed for these different PNC tasks range from rhythmic rolling planning with frozen periods and predetermined objectives to reactive project-based planning with open objectives. Broadly, shorter time horizon planning tasks tend to be more structured (Ilie-Zudor, & Kemény et al., 2017, p. 64; Klein & Scholl, 2012, pp. 19–20) and larger, more mature organisations tend to have more structured planning processes (Lester, & Parnell et al., 2003, p. 343). The organisational functions tasked with planning and deciding also vary organisation.

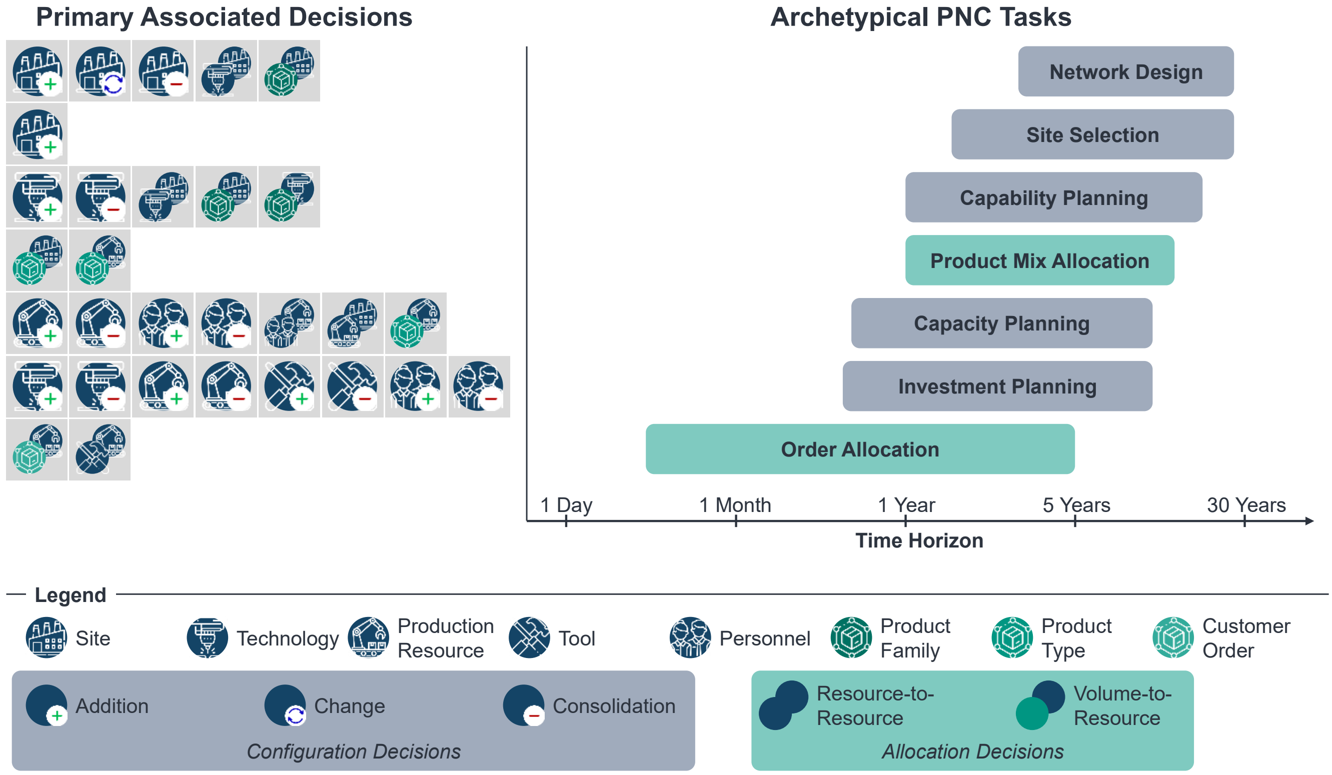

Figure 2-7: Overview of Archetypical PNC Tasks

The heterogeneity within the PNC tasks results in a need for individually adapted processes and tools (Chandra & Grabis, 2016, p. 90; Guimaraes, & Igbaria et al., 1992,

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[5] For example, order allocation can refer to processes with multi-year time horizons in the aviation industry (cmp. Buergin, & Blaettchen et al., 2019)) or a few months for automotive products (cmp. Buergin, & Hammerschmidt et al., 2019).

[6] For example, product mix allocation and capacity planning can functionally refer to the same process, though one is focused on the product side and the other on the resource side (Lin, & Chen et al., 2007; Menezes, & Ruiz-Hernandez et al., 2024).

p. 426). Instead of relying on a strict type classification, PNC tasks can also be described based on the infrastructure view of production introduced in 2.1.2. As shown in Figure 2-7, every PNC task is characterised by the set of resources it configures, which determines the task's significance, frequency, and time horizon.

2.2 Decision Support

Whereas the previous section focused on the object under consideration in this work, this section focuses on decision support, which is the objective of this work. First, the basics of decision-making are illustrated in Section 2.2.1. Next, decision support systems (DSS), the category of systems this work concentrates on, are explored in 2.2.2. One of the core elements of DSSs in production networks is models of real systems. Thus, 2.2.3 introduces the system-theoretic background of models and their creation process. The heterogeneity of production network configuration tasks, as illustrated in 2.1.4.2, is reflected in the multiplicity of different methods used to perform them, which are introduced in 2.2.4. Finally, 2.2.5 discusses the implementation and evaluation of DSSs in industrial organisations.

2.2.1 Decisions & Decision Making

Decision-making denotes the selection of one or multiple non-exclusive alternatives from a set of available alternatives (Bozorg-Haddad, & Loáiciga et al., 2021, p. 1; Hitomi, 1996, p. 38). In production management, the terms planning and decision-making are often used interchangeably (Klein & Scholl, 2012, p. 1). Whereas decision-making is more focused on a single decision, planning includes all decisions necessary to transition from a non-satisfactory state to a desired state. This difference is mainly semantic. Thus, both terms will be treated as synonyms in the following. According to H. A. Simon (1960, pp. 1–4), the decision-making process comprises three phases: *intelligence*, *design*, and *choice*. Intelligence describes examining the environment in which a decision is made, including recognising decision-worthy situations. Design is developing and analysing alternatives, i.e., possible courses of action. Choice refers to the selection of one course of action. Others have expanded upon these three phases, particularly in the context of model-based decision-making. Domschke and Scholl (2008, p. 26) propose (i) *identification*, (ii) *problem analysis*, (iii) *objective definition*, (iv) *prognosis*, (v) *alternative search*, (vi) *alternative evaluation* and (vii) *decision* as the phases to describe decision making. Decision processes commonly include overlapping phases and iterations within this framework (Domschke & Scholl, 2008, p. 25). Similar approaches, differing slightly in terms of the exact phases, exist in the literature (Klein & Scholl, 2012, p. 13; Nyhuis, 2008, pp. 8–9; Ratliff & Nulty, 1996, p. 39). In the following work, a slightly adapted version of Domschke and Scholl's decision-making process shall be used, as shown in Figure 2-8. In it, phases i-iii are aggregated under problem definition, as this work focuses primarily on the design and choice parts of H. A. Simon's model. Furthermore, scenario generation (iv) and configuration generation (v) are considered parallel strains. Finally, the iteration of the scenario and configuration generation is explicitly considered.

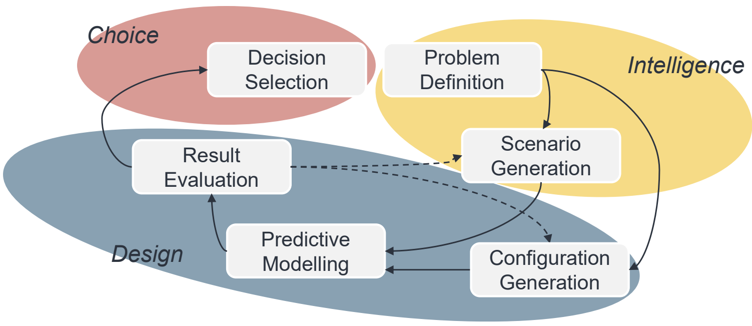

Figure 2-8: Decision-Making Process in this Work and Relation to Decision-Making Phases of H. A. Simon (1960)

Different decision processes may be triggered in distinct ways depending on the organisation. Generally, scheduled and reactive, event-driven planning may be differentiated. In scheduled planning, decisions are made as a part of rolling or hierarchical planning sequences (Fleischmann, & Meyr et al., 2015, pp. 73–74). In rolling planning, decisions are made concerning a planning horizon (Fleischmann, & Meyr et al., 2015, p. 73). Then, after a part of the planning horizon, a new plan is created with updated input on developments from the previous period (Fleischmann, & Meyr et al., 2015, p. 73). In a hierarchical planning structure, the decisions regarding a system are divided into a hierarchical structure where long-term, aggregated, and comprehensive decisions are made at the top, and short-term, detailed, specific problems are made at the bottom (Fleischmann, & Meyr et al., 2015, p. 75; Ilie-Zudor, & Kemény et al., 2017, p. 70). Between the different levels, directives (top-down) and feedback (bottom-up) are exchanged to ensure that overall planning is consistent (Stadtler, 2015, p. 25). This structure is designed to effectively address the complexity of planning large systems (Stadtler, 2015, p. 26). Event-driven planning, by contrast, is updated whenever new crucial information that deviates from the previous assumptions becomes available

(Fleischmann, & Meyr et al., 2015, p. 74). Decision processes may be triggered by deviations between target and actual performance or by changes in available alternatives, data, or preferences of decision makers (Domschke & Scholl, 2008, pp. 26–27). These changes can be detected and addressed based on predetermined rules or subjectively based on decision-makers' assessments. Figure 2-9 provides an overview of these different decision-process triggers.

According to Klein and Scholl (2012, p. 15ff) the planning subject, the level of information, the frequency, the scope in terms of functional and application area, the factual and temporal reach, and factual and temporal coordination may be used as additional categories to classify planning processes.

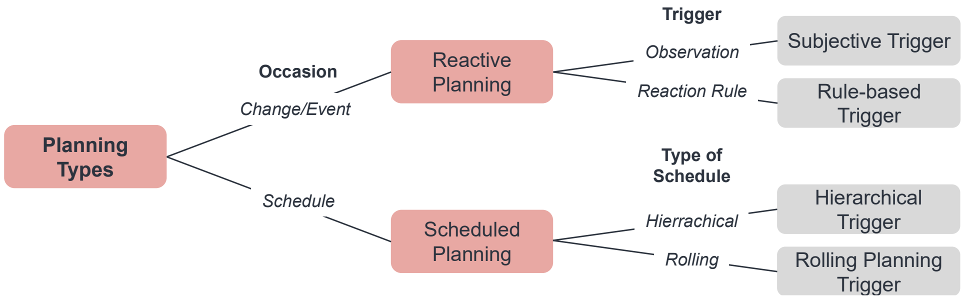

Figure 2-9: Types of Decision Process Triggers and Schedules

A common standard to describe and formalise business processes, which planning processes are a part of, is the Business Process Model and Notation (BPMN) (Dumas, & La Rosa et al., 2013, p. 17; Weske, 2019, pp. 6–7). Using BPMN processes can be formalised into logical sequences and related to information artefacts, resources, and stakeholders (Dumas, & La Rosa et al., 2013, p. 63).

In terms of the decision-makers, individual and group decisions can be distinguished (Klein & Scholl, 2012, p. 18). In practice, multiple people often make decisions as a collaborative effort. A common approach to describe the rights and obligations of parties involved in planning and other tasks is the Responsibility Assessment Matrix (RAM), which assigns the roles responsible, accountable, contributor, and informed to combinations of parties and tasks (Cabanillas, & Resinas et al., 2018; Costello, 2012). In the following, the term decision-making committee (DMC) will be used as a stand-in for a not further specified decision-making group, composed of one or more people, with the responsibility to weigh the available alternatives and ultimately decide.

2.2.2 Decision Support Systems

As the term Decision Support System (DSS), which was initially coined by Gorry and Morton (1971), implies, they are computerised systems that aid humans in making decisions (Power, & Burstein et al., 2011). They represent a subsection of management support systems (MSS), which support managerial actions and decision-making (Clark, & Jones et al., 2007, p. 579). More broadly, they can also be characterised as one type of information system (IS). DSSs are characterised by the following properties (Power, 2002):

(1) DSSs are explicitly designed to facilitate decision processes,
(2) DSSs should support, not automate, decision-making (Angehrn & Jelassi, 1994, p. 269),
(3) DSSs should respond quickly to the changing needs of decision-makers.

DSSs specifically support semi-structured and semi-routine decisions (Power & Sharda, 2007). DSSs can demonstratively improve the quality and speed of decision-making. A characterising feature of DSSs is their interdisciplinary origins, which may have contributed to their success (Angehrn & Jelassi, 1994, p. 268). DSSs are designed for users with limited modelling knowledge, so they can interact with the systems but typically cannot develop them themselves (Sprague, 1980).

Various taxonomies for DSSs have emerged over five decades of research on such systems, most notably by Alter (1977), Carlson (1978), Sprague (1980), and Power (2002). Alter differentiates seven types of systems from most data-oriented to most model-oriented: *file drawer systems*, *data analysis systems*, *analysis information systems*, *accounting models*, *representational models*, *optimisation models*, and *suggestion models* (Alter, 1977). DSSs need to be differentiated from expert systems (ES), which focus on capturing the knowledge of domain experts and making it accessible to other users (Jayaraman & Srivastava, 1996; Yoon, & Guimaraes et al., 1995, p. 84).

According to Power (2002), DSSs can also be categorised by their primary focus, i.e., what they are 'driven' by into *data-driven*, *model-driven*, *knowledge-driven*, *document-driven*, and *communications-driven*. In the following, this work focuses on model-driven DSS, where one or multiple models make up the primary component of the DSS. A model-driven DSS may include several components, each providing different functionalities. The core functionalities any such DSS must provide are (i) user interaction, (ii) data storage, (iii) calculation, and (iv) communication between the components. These functionalities, which are portrayed in Figure 2-10, may be implemented in separate modules but can also be realised in one unified tool.

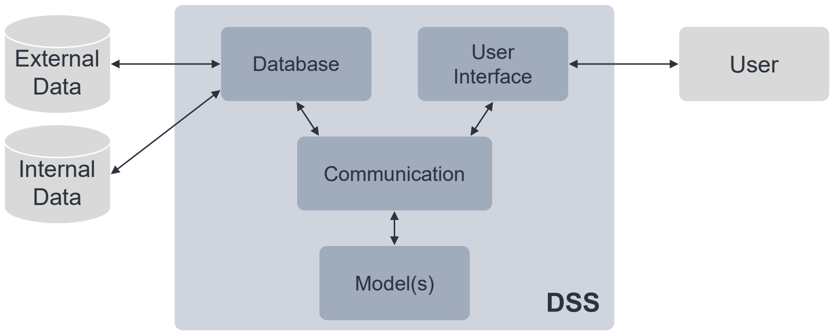

Figure 2-10: Components of Decision Support Systems according to Power (2002)

Throughout the decades of DSS research, authors have been concerned with highlighting desirable characteristics that should be considered in their design. Angehrn and Jelassi (1994, p. 269) argue that they should address three main foci:

(1) *Conceptual focus*: DSSs should address the nature of individual and organisational decision-making processes.

(2) *Methodological focus:* DSSs should integrate existing and evolving computer-based tools, techniques, and systems into human decision-making.

(3) *Application-oriented focus:* DSSs should address the real organisation's needs and extend decision support to business teams.

Angehrn and Jelassi (1994, p. 270) further call for additional usage focuses for DSSs outside of the choice phase, as defined by H. A. Simon (1960). They specifically mentioned DSS for learning and for challenging assumptions and strategies pursued in decision-making (Angehrn & Jelassi, 1994, p. 270). Jayaraman and Srivastava (1996, pp. 29–30) stipulate eight use case categories for DSSs[7]: (i) consulting, (ii) designing, (iii) diagnosis, (iv) interpreting, (v) monitoring, (vi) planning, (vii) predicting, and (viii) teaching. These categories are portrayed in Figure 2-11.

[7] Though these use cases are focused on ESs, they may also be applied to DSSs.

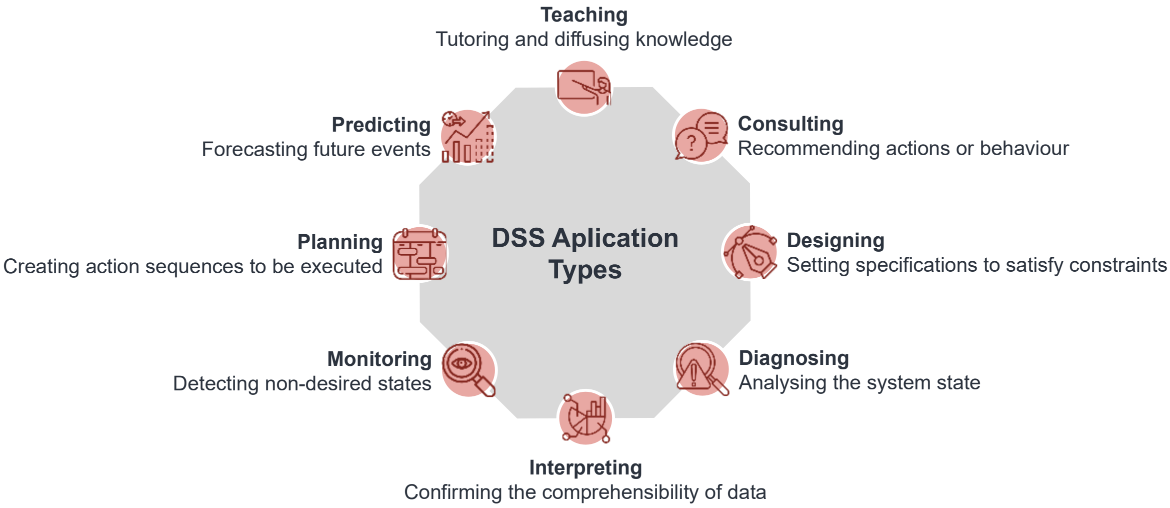

Figure 2-11: DSS Applications According to Jayaraman and Srivastava (1996, pp. 29–30)

In addition to archetypal DSSs, which focus on a single type of decision and a specific type of user, more organisationally integrated concepts have been proposed. Group decision support systems (GDSS) facilitate decisions by groups with diverse backgrounds and perspectives (Angehrn & Jelassi, 1994, p. 271; DeSanctis & Gallupe, 1984, p. 3). GDSS design is, first and foremost, concerned with the interactive communication between the members of the decision-making group (Nunamaker & Deokar, 2008, p. 391). Another concept is organisational decision support systems (ODSS), which focus on organisational activities involving multiple actors (George, 2008, pp. 417–418). ODSSs may be composed of multiple DSSs or components thereof that communicate with each other to facilitate organisational tasks (George, 1991, p. 114).

2.2.3 Models & Modelling

As the previous section indicated, this work focuses on models as a means of decision support. This section introduces the model concept, referencing its relation to the concept of a system and its system-theoretical underpinnings. It then briefly outlines different categories of models before presenting the process by which models are designed and used, consisting of conceptual modelling, implementation, and experimentation. Subsequently, the issues of model verification, validation, and calibration are introduced. Finally, systems comprised of multiple models and their interactions are discussed.

2.2.3.1 Systems

The term system refers to the collection of elements interacting with each other that are separated from the system environment via a system boundary (Klein & Scholl, 2012, p. 31). This boundary is, by definition, permeable to inputs originating in the system environment and system outputs. The concept of systems has found widespread practical application across nearly all scientific disciplines. What is and what is not part of a system is an arbitration of the observer, subject to their predisposition. In many situations, systems with a hierarchical structure can be observed, i.e., systems whose elements are themselves systems.

The notion of systems is closely linked to the concept of complexity. According to H. A. Simon (1962, p. 468), complex systems are “made up of a large number of parts, that interact in a non-simple way, […] such that given the properties of the parts and the laws of their interaction, it is not a trivial matter to infer the properties of the whole”. This highlights the two main causes of complexity: the multitude of elements and the diversity of their interactions. Complexity in systems is linked to the occurrence of emergent behaviour (Bennet & Bennet, 2008, p. 6) but also to non-predictability and, specifically in technical systems, increases in operational costs.

2.2.3.2 Models

According to Stachowiak (1973, pp. 131–133), models are (i) representations of some original, (ii) simplify the original based on the desires of the model creator, and (iii) are only valid for a limited purpose, time, and operations. As such, models are necessarily built for a specific purpose and may fulfil that purpose to varying degrees. Following this notion, it becomes apparent that models, their target systems and their purpose towards either a user or an interpretation form a triadic relationship (Knuuttila, 2005, p. 1261). Therefore, when applying models for decision-making, choices can and have to be made regarding the model's design (Maier, & Eckert et al., 2017, p. 6). The effort necessary to create models is typically linked to the model quality, i.e. they should be "as abstract as possible and as precise as necessary" (Nyhuis, 2008, p. 15). The process by which the abstraction of the natural world into a specific model is implemented is further discussed in subsection 2.2.3.4. In the following, the term model will be used synonymously with the concept of a quantitative model, i.e., a model defined by mathematical axioms that can be computerised.

2.2.3.3 Model Types

The idea of distinguishing models by the degree to which the system's outputs can directly determine the decision, later termed *analytical capability* (AC) (Medina, & Umpierrez et al., 2021), has proven very useful. In recent literature, typically, four classes are distinguished, which can be attributed back to the purpose-oriented categorisation by Alter (1977). With increasing levels of analytical capability comes an increased level of abstraction (Arnold, & Isermann et al., 2008, p. 41). The first type, *descriptive models,* represent the state of a system without indicating how it may behave or change. *Diagnostic models* describe the fundamental relationships between the behaviour of different system aspects and the system environment. *Predictive models* can estimate the behaviour of a system under a given set of conditions. *Prescriptive models* go one step further and deduce how a system should be designed to achieve a desired behaviour given a set of circumstances. Typically, the two levels with the highest analytical capability, *predictive* and *prescriptive* models, are the ones considered for model-based DSS (Liang, & Lee et al., 2008). Notably, the analytical capability can be mapped to the so-called structural deficiency[8] of a particular decision problem (Arnold, & Isermann et al., 2008, pp. 39–41). Arnold et al. (2008, pp. 39–43) argue that predictive models may support decisions which are effect-complete but evaluation-defective, whereas prescriptive models require evaluation and target-complete problems. Vaidya and Seetharaman (2007, p. 30) state, that several aspects, such as data used, the decision process, decision-making styles, organisational structure and culture, power and politics, and time pressures, can lead to unstructuredness in decisions, thus complicating the use of prescriptive models. Furthermore, prescriptive models may not always be desirable, as stated by Ziegler et al. (2019, p. 224). An overview of the model types and their characteristics is provided in Figure 2-12.

In addition to their analytical capability, quantitative models are often classified according to time variance as *static* and *dynamic,* and according to the degree of predetermination as *deterministic* and *stochastic (Klein & Scholl, 2012, pp. 32–33)*. Whereas static models assume the temporal development of the system to be irrelevant or abstract, dynamic models incorporate the temporal change of model elements and the

[8] Here, structural deficiency refers to the degree to which a problem deviates from a well-defined problem, which by definition can be solved efficiently and definitely, as shown by Adam (1980, pp. 50–52).

corresponding reactions (Klein & Scholl, 2012, p. 39). Deterministic models assume that any quantity portrayed in the model is well-defined and known, and thereby, every change in the system or its environment is predetermined. Stochastic models assume that a subset of the quantities in the model is unknown and can only be estimated (Klein & Scholl, 2012, pp. 38–39). Thereby, modelling results can only make statements about the likelihood of occurrence. Though some analytical models[9] exist that represent time and likelihoods as continuous functions, most models relevant to the topics discussed here discretise both temporal change and uncertainty to limit complexity.

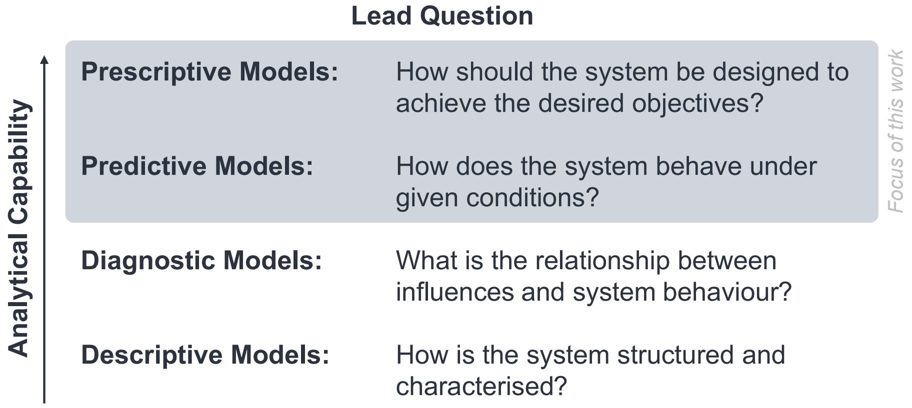

Figure 2-12: Categorisation of Models by Analytical Capability

2.2.3.4 Multi-Model Systems

The systems concept inherently contains a sub-structuring into sub-systems. As recognised in the engineering design field, this can be described as systems-of-systems (SoS), where each subsystem is governed by specific rules (Weilkiens, & Lamm et al., 2016, pp. 246–248). Modelling complex SoS may require the combination of multiple distinct models. This approach is common in engineering design, where model-based systems engineering is a whole field focused on disaggregating complex systems into subsystems which can be described using different, domain-specific modelling approaches (Fishwick & Zeigler, 1992). In these approaches, the interfaces between models and the assignment of responsibilities are primary concerns. A core principle in such systems realised in product lifecycle management (PLM) systems is to formalise the parameters that describe interfaces between different models and store them in a

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[9] Although the term is used differently in different contexts, here it refers to analytically solvable models, i.e., when for a model $f(x,p) = z$ a function $f^{(AS)}$ exists which satisfies $f^{(AS)}(o(z),p) = x$, where z denotes the outcome, $o(z)$ the preferences regarding that outcome, and p the parameters of the problem.

common database (Grieves, 2005). For this purpose, the Systems Modelling Language (SysML) is commonly employed (Weilkiens, & Lamm et al., 2016, p. 202).

Another field where multi-model systems are commonly applied is weather and climate prediction. Multiple predictive models are combined in model ensembles to provide a range of predictions for specific developments. These ensembles aim to address model uncertainty by employing multiple alternatives. (Tebaldi & Knutti, 2007)

In production systems, some research has focused on combining different types of predictive models. Morgan et al. (2017, pp. 911 ff.) distinguish six principal interaction forms of predictive models: (i) isolated, (ii) parallel, (iii) sequential, (iv) enriching, (v) interacting, and (vi) integrating, depending on the type of information exchanged between them. Figure 2-13 illustrates these model interactions.

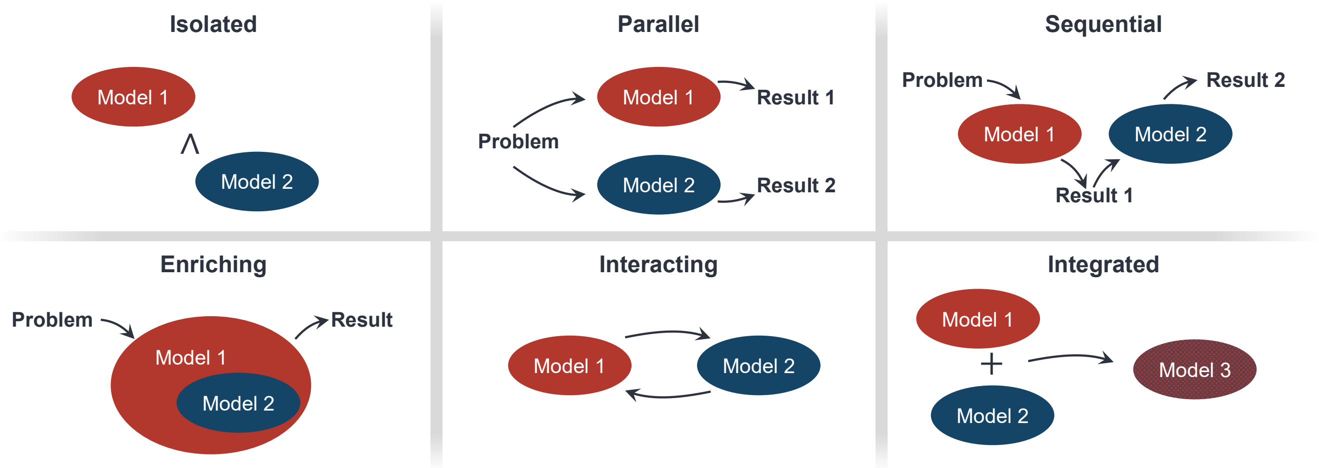

Figure 2-13: Types of Interactions between Models according to Morgan et al. (2017)

Brailsford et al. (2019, pp. 723–724) adapt and expand this framework to include the phases of the modelling lifecycle. For the combination of predictive and prescriptive models, Figueira and Almada-Lobo (2014, pp. 127 ff.) develop a taxonomy to describe several different interaction forms. They distinguish four types of simulation purposes: (i) evaluation function, (ii) surrogate model construction, (iii) analytical model enhancement, and (iv) solution generation. Furthermore, they find four types of hierarchy between the models. Amaran et al. (2016) collect and classify methods for the optimisation of an underlying simulation model, highlighting (i) discrete optimisation via simulation, (ii) response surface methodologies, (iii) gradient-based methods, (iv) sample-path optimisation, (v) direct search, (vi) random search, (vii) model-based methods, and (viii) Lipschitzian optimisation.

2.2.3.5 Modelling

"Modelling is the purposeful process of abstracting and theorising about a system, and capturing the resulting concepts and relations in a conceptual model" (Tolk & Turnitsa, 2012, p. 2). Based on those conceptual models, an executable model can be implemented that allows users to experiment and solve a specific problem (Sargent, 2010, pp. 168–169). This overall idea is captured in multiple different descriptions of modelling processes. Figure 2-14 shows the modelling processes proposed by Sargent (2010), distinguishing three main phases: (i) conceptual modelling, (ii) implementation, and (iii) experimentation. These phases are discussed in more detail in the following sections.

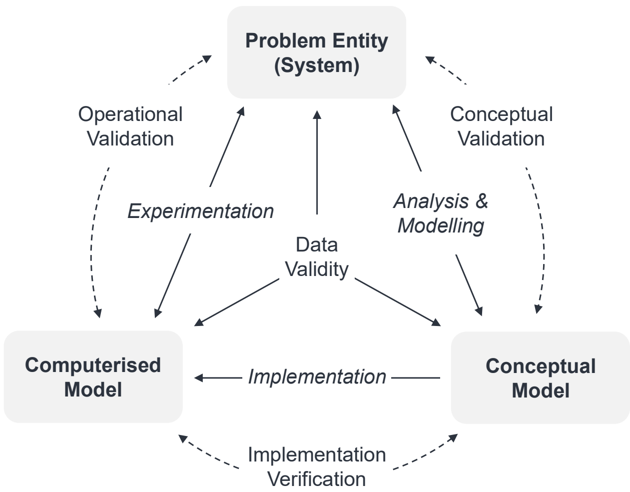

Figure 2-14: Modelling Process According to Sargent (2010)

2.2.3.5.1 Conceptual Modelling

Sagasti and Mitroff (1973, p. 698) point out that conceptual modelling or conceptualisation may be the most impactful yet least studied step of modelling. Utilising Churchmans (1971, pp. 61–161) analysis of different inquiry systems, they assert that the predisposition of the model builder strongly influences the construction of a conceptual model. Sagasti and Mitroff (1973, p. 702) go so far as to state that conceptual modelling is more art than science and may remain that way. According to Robinson (2015, pp. 1823–1824), a conceptual model contains the content of the model, made up of its inputs, outputs and its objectives, which may be manipulated concerning the *scope of the model* and the *level of detail* it represents. Furthermore, the conceptual model includes the *assumptions* made regarding the target system and the *simplifications* incorporated in the model (Robinson, 2015, p. 1825). Table 2-1 illustrates these aspects used to structure the conceptual modelling approach.

Table 2-1: Aspects of Conceptual Models According to Robinson (2015)

Scope	Level of detail	Assumptions	Simplifications
Breadth of the target system to be incorporated in the model.	Granularity of the representation for each model component	Beliefs about the behaviour of the target system and its environment.	Omissions of elements and behaviours made to accelerate model development and use.

Based on these aspects, conceptual modelling follows the following steps according to Robinson (2008, p. 291): (i) understanding the problem situation, (ii) determining the modelling and general objectives, (iii) identifying the model outputs, (iv) identifying the model inputs, (v) determining the model content (scope and level of detail) and identifying any assumptions and simplifications. Concerning the last step, various abstraction approaches may be applied, which modify either the boundary, behaviour, or form of the model (Frantz, 1995, p. 1415).

The choice of models can also be based on the notion of structural defects of the decision problem. According to Klein and Scholl (2012, pp. 54–56) problems can be defective in (i) demarcation, (ii) effect, (iii) evaluation, (iv) target setting, and (v) solution. Different models and modelling techniques should be applied depending on the present structural defects. This approach considers planning mainly as a process of model-based structuring (Klein & Scholl, 2012, p. 56).

2.2.3.5.2 Implementation

Whereas much of the discussion in modelling is focused on designing models that fit the problem characteristics, conceptual modelling often only takes up a fraction of the time. Instead, data acquisition and model generation, which are part of implementation, may take up to 50% of the time in model-based decision-making (Acél, 1996, p. 15; Müller-Sommer & Straßburger, 2010, pp. 61–62). Implementation refers to the translation of a conceptual, non-executable model to an executable instance. The relation between the conceptual and the executable model is a one-to-many, as there are infinitely many valid realisations of a conceptual model. Thus, the implementation needs to take into account practical concerns, such as the availability and familiarity of modelling tools and the abilities of developers. The goal in implementation is typically to realise the desired value-add as quickly as possible with the lowest possible resource spend. Additionally, implementations should be future-proof in the sense that they may be used for a long time, are easy to adapt to changes, and further development is possible.

2.2.3.5.3 Experimentation

Experimentation describes the use of predictive or prescriptive models to attain the desired knowledge regarding the system behaviour and support decision-making. In experimentation, the uncertainties and limitations of the model and the available information must be taken into account. Verein Deutscher Ingenieure [VDI] (2014), who focus on the use of simulation propose a four-part procedure consisting of (i) experiment planning, (ii) experiment conduct, (iii) meta-modelling, and (iv) analysis & prognosis.

Design of experiments (DoE) describes a method to systematically plan, conduct, and analyse experiment series (Antony, 2014, p. 8), aimed at minimising the number of necessary experiments while producing the most meaningful statements about the examined decision possible (Dean, & Voss et al., 2017, p. 1 ff.). Herein, DoE prescribes the selection of a range of input parameters $\boldsymbol{x} \in X_s^{(IP)}$ to best characterise the behaviour of the system s with the behaviour $\boldsymbol{f}_s(\boldsymbol{x}) = \boldsymbol{z}$, where $\boldsymbol{z}$ denote the response of the system.

2.2.3.6 Verification, Validation & Calibration

A model may be considered valid if it represents the target system within an acceptable range of accuracy with respect to the purpose of the model (Sargent, 2010, p. 166). Thus, validation and verification are the processes by which the validity of the model can be assumed with sufficient confidence (Sargent, 2010, p. 167). Herein, validation is focused on ensuring the model as a theoretical construct appropriately reflects the behaviour of the target system, referencing the underlying theories used to develop the model (Sargent, 2010, p. 171). Verification ensures that the implemented model correctly follows the stipulations of the conceptual model (Sargent, 2010, p. 171). A number of techniques can be used to perform validation and verification, either by the model developers, prospective users or independent parties (Sargent, 2010, pp. 167–172). As Figure 2-14 shows, these activities should encompass conceptual and operational validation, validation of the data used, and verification of the implementation.

Although calibration is related to verification and validation, it focuses on aligning model behaviour with target system behaviour, rather than scrutinising the alignment. Calibration in the context of quantitative modelling is the process of adjusting or determining internal parameters $\boldsymbol{p}_m$ of a predictive model m which follows $\boldsymbol{f}_m\colon (\boldsymbol{x}, \boldsymbol{p}_m) \rightarrow \boldsymbol{z}$, where $\boldsymbol{x}$ denotes inputs into the model and $\boldsymbol{y}$ denotes model responses. Calibration functions use sets of known inputs and outputs $l_i = (\boldsymbol{x}_i, \boldsymbol{z}_i) | i \in I_{\mathrm{L}}^{(IO)}$ of the real system to determine $\boldsymbol{p_m}$. Two calibration methods can be distinguished: (i) direct calibration methods, which determine one value for each parameter, and (ii) Bayesian calibration, which determines the probability density function (PDF) for a parameter (Xu, 2017, p. 28). Calibration methods are especially important if parameters of a model cannot be directly inferred from real-world data. Though Bayesian calibration is preferable in terms of accuracy, it requires more complex calibration functions (Xu, 2017, p. 29).

2.2.4 Methods in DSS

Various methods can be used as part of a DSS. These methods contribute to the overall decision-making process and are either part of or contribute to the operation of models underlying a DSS. Thus, they may be structured according to their contribution. Figure 2-15 shows the decision-making process employed in this work, as well as five groups of methods that may be utilised in it. *Scenario generation methods* help describe the condition and development of the environment of the system under consideration. *Configuration methods* aid manual decision processes using predictive models by developing a set of alternatives. *Predictive methods* are used to capture and predict the behaviour of a system under consideration. *Prescriptive methods* are used to identify preferred alternatives, given a set of objectives, in conjunction with predictive methods. *Decision selection methods* help resolve objective conflicts and translate solutions found through model-based experimentation into decisions. *Metamodeling methods* approximate predictive and prescriptive models to save computational resources.

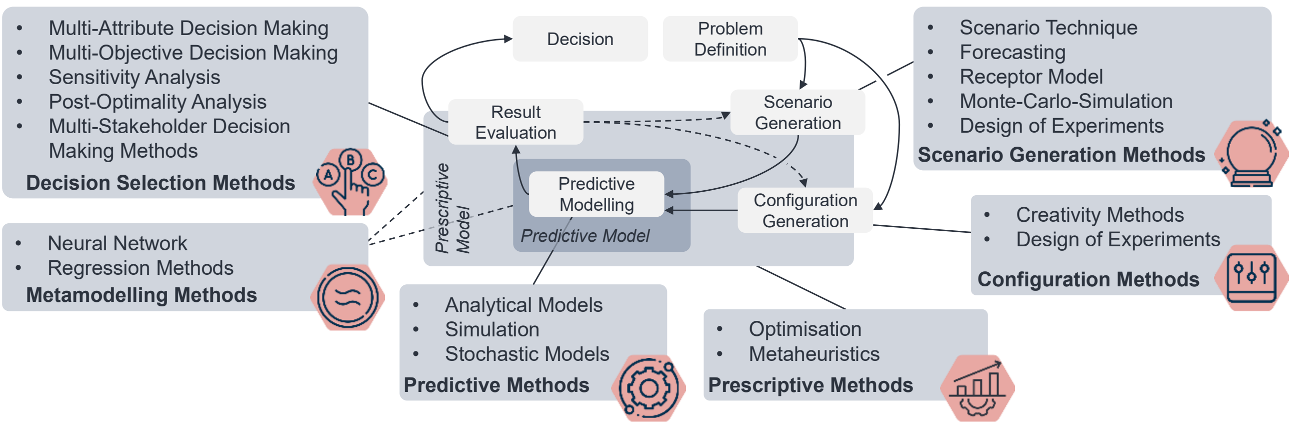

Figure 2-15: Methods in DSS in the Model-Based Decision-Making Process

Table 2-2 provides an overview of the most relevant methods for model-based DSS in PNC tasks. A more detailed description of each method, along with pertinent references, is provided in Appendix A1.

Table 2-2: Methods for Model-Based DSS and their Contribution

Type	Category	Method	Description
Decision Selection	Multi-Attribute Decision Making	Value Measurement	Determine a quantitative value score for each alternative
		Reference Level	Identify alternatives with proximity to an aspiration level
		Outranking	Determine a ranking between alternatives
	Multi-Objective Decision Making	a-Priori Weighing	Determine a preferred decision based on previously specified and weighed objectives
		a-Posteriori Weighing	Allow decision-makers to select a decision given a Pareto front
		Interactive Approaches	Allow decision makers to interact with the decision and adjust weights
	Sensitivity Analysis		Determines the effect of changes to parameters on the results
	Post-Optimality Analysis		Determines the costs of constraints
	Multi-Stakeholder Decision-Making Methods		Enable decision-making in multi-perspective groups
Meta-modelling	Regression Methods	Gauss Process Regression	Modelling of results including a trend and a Gauß process
		Response Surface Models	Modelling results using polynomial terms
		Multi-Adaptive Regression Splines	Modelling results as piece-wise linear terms
	Feed Forward Neural Networks		Modelling results as a series of weighted activation functions
Predictive Methods	Deterministic Models	Linear Models	Modelling as a linear function
		Mixed Integer Linear Models	Modelling as a linear function with an integer variable
		Quadratic Models	Modelling with a quadratic function
	Simulation	Discrete Event Simulation	Models with discretisation of time by a dynamic event-schedule and with leaping state changes
		Agent-Based Simulation	Models of systems composed of multiple interacting agents
		System Dynamics	Models with interval-based discretisation of time to solve differential equations
	Stochastic Models		Modelling of a series of uncertain developments and decisions
Scenario Generation	Scenario Techniques		Creation of consistent scenarios for future development
	Forecasting		Modelling of external development based on available historical data
	Receptor Model		Aggregation of uncertain external influences to input parameters
	Monte-Carlo Simulation		Random instantiation of distributions
	Design of Experiments		Systematic evaluation of the parameter space while minimising the number of experiments
Configuration	Creativity Techniques	Idea Generation	Open, creative generation of ideas, typically in groups
		Systematic Alternative Construction	Systematic manual investigation of the design space
		Distributed Expert Mining	Synthesising expert inputs for decision alternatives
	Design of Experiments		Systematic evaluation of the parameter space of alternatives while minimising the number of experiments
	Constraint & Objective Variation	Parameter & Sensitivity Exploration	Assessing the impacts of parameters to create new alternatives
		Pareto Front Exploration	Systematic analysis of the entire Pareto front to find tipping points
		Constraint Relaxation	Relaxing constraints to allow models to find constraints worth breaking
Prescriptive Methods	Optimisation	Linear Optimisation	Exact optimisation of a linear model
		Mixed Integer Optimisation	Heuristics-based optimisation of a model partially consisting of integer variables using the associated linear/quadratic model
		Dynamic Optimisation	Exact optimisation of a model with states by dividing it into subproblems
		Quadratic Optimisation	Exact optimisation of a model with a quadratic objective function
		Stochastic Optimisation	Optimisation on a discretised set of uncertain developments
	Metaheuristics	Population-based Approaches	Approaches to find solutions based on a population of alternatives
		Trajectory-based Approaches	Approaches to find solutions based on a path through the solution space and local conditions

2.2.5 Implementation & Evaluation of DSS

In the following, approaches to DSS development and deployment are discussed, as well as the evaluation of DSS, ensuring a positive effect on the employing organisation.

2.2.5.1 DSS Development & Implementation Process

The development and implementation of a DSS can be viewed as a software project. Software projects include (i) development, (ii) maintenance, (iii) organisation, (iv) support, and (v) experimental projects (Wieczorrek & Mertens, 2008, 9). As the DSSs considered in this work are largely developed by or with the employing organisation, development and organisation projects are relevant. Several factors can influence the success of such projects, e.g. top-management engagement, user involvement, experience of project leadership, alignment with the organisation's strategy, limited project size, standardised software infrastructure, management of requirements, a standardised project procedure, and reliability of cost estimates (Wieczorrek & Mertens, 2008, pp. 18–23).

For DSS specifically Guimaraes et al. (1992) found that success is determined by user involvement and training, top management support, information sources, the level of the managerial activity supported, and characteristics of the task. Thus, user involvement and transparency seem to be important factors in creating successful DSS. Another crucial determinant for DSS success seems to be task specificity (Power & Sharda, 2023, p. 1407), as DSS for multiple different tasks can be inversely related to user satisfaction (Guimaraes, & Igbaria et al., 1992, p. 426). According to Clark et al. (2007, pp. 603–606) scientific literature also largely agrees that problem space match is crucial for the success of MSS and, by extension, likely for most DSS. Furthermore, user satisfaction with DSS seems to improve with less structured tasks, indicating that DSS should target scenarios with high degrees of uncertainty, where they can provide the most support (Guimaraes, & Igbaria et al., 1992, p. 426).

To realise the desired DSS, several procedure models can be applied. *Incremental procedures* are designed to provide initial value to users after a short time. In it, projects are planned in their entirety but realised in partial steps. Examples of incremental procedures include the release-based and V-model approaches. For more modest projects, a *conceptual procedure* is suitable, which organises the work in one thread from abstract and conceptual to detailed and implemented. For IT projects realised by external service providers, an *empirical procedure* based on experiences gathered with the application of existing ISs is applicable. (Wieczorrek & Mertens, 2008, pp. 64-75)

In large organisations, where the potential user base is distributed across multiple sites, realising an effective adoption of new ISs is a challenge (van Fenema, & Koppius et al., 2007, pp. 586–587). Adoption is the stepwise process of assuming an innovation (Homburg, 2017, p. 641). According to Rogers (2003) the innovation-decision process, that informs the adoption decision, is structured in five phases: (i) knowledge, (ii) persuasion, (iii) decision, (iv) implementation, and (v) confirmation. Rogers (2003) argue that champions, charismatic individuals who support and propagate innovations, are crucial to their success. In studies by other authors, the concept of key-users, who interact intensively with the development team and provide guidance to other users, has proven successful (van Fenema, & Koppius et al., 2007, pp. 588–595).

2.2.5.2 DSS Value Assessment

As the previous section showed, the effort and costs necessary to implement a DSS successfully are not negligible. For organisations, it is crucial to examine whether such an investment is worthwhile. As the resources available for implementation are usually limited and multiple DSS could be pursued, this is not only a value problem but rather a prioritisation problem. Consequently, Marsden and Pingry (1993) propose a DSS portfolio management approach, where different potential DSS are evaluated regarding the benefits they provide across a set of identified problems. Fitting DSS options may then be chosen to maximise the added value to the organisation. A similar approach is proposed by Lederer (2008, p. 342). Similar approaches to prioritisation problems can be found across other domains. Liebrecht (2020), for example, use the analytic hierarchy process (AHP) and TOPSIS to assess different development paths in a company's Industry 4.0 portfolio. Generally, multi-attribute decision-making (MADM) approaches are suitable for this type of problem. In the following paragraphs dimensions of benefits and costs associated with DSS are discussed.

As Figure 2-16 illustrates, the primary benefits of DSS lie in improvements to *decision quality* and the *decision-making process* itself (Pick, 2008, p. 720). Additionally, they can lead to secondary benefits such as knowledge transmission and learning in the organisation (Tomblin, 2008). Improvements in decision quality should be measured against the objectives relevant to this decision. Benefits for the decision-making process can include reduced effort, higher decision speed, increased transparency, increased standardisation, and higher employee satisfaction (Pick, 2008, pp. 723–724).

Figure 2-16: Primary Benefits of Decision Support Systems

Several different frameworks to assess the value of a DSS using specific measures exist (Grover, & Jeong et al., 1996; Pieptea & Anderson, 1987; Rhee & Rao, 2008). As an a priori estimation of benefits is often difficult, prototypes can be used to gauge potential benefits (Pick, 2008, p. 726). However, even prototype-based estimations are limited, as the achieved benefit can often only be measured in terms of the existing evaluation functions inherent to the existing decision process or the prototyped DSS. Evaluating realised improvements would require large-scale analysis of decisions with and without the DSS, which is hardly feasible in PNC tasks. DSS can be used to reassess past decisions, establishing potential benefits (Pick, 2008, p. 725).

Especially for internal software development and DSS, cost estimation is challenging (Lederer, 2008, p. 339). A variety of software development cost estimation techniques exist, which can be divided into (i) parametric models, (ii) expertise-based techniques, (iii) learning-oriented techniques, (iv) dynamics-based models, (v) regression-based models, and (vi) composite-Bayesian techniques (Boehm, & Abts et al., 2000, pp. 177–178). In the absence of empirical data, expertise-based techniques can be used, which include the Delphi technique, work breakdown structure, and planning poker (Boehm, & Abts et al., 2000, pp. 192–194; Cohn, 2005, pp. 56–59).

2.3 Data, Information, & Information Systems in Production

As discussed before, data availability and data quality play a crucial role in model-based decision-making. In this section, the concepts of data and information are introduced in 2.3.1, as well as data models used to structure data and databases used to store them in 2.3.2. Subsequently, data models and information systems with particular relevance to production and PNC tasks are illustrated in 2.3.3.

2.3.1 Data & Information

Data are sets of symbols in a rule-based system called syntax (Krcmar, 2015, p. 11). Given a context in which the data is understood, they become information (Krcmar, 2015, p. 11). By evaluating, connecting and classifying information, knowledge is created, which, in contrast to information, has a long-term character and allows judgments (Piller, 2006, p. 19).

In the industrial context, four types of data can be distinguished with respect to their relation to the production system (Caridi, & Crippa et al., 2010, p. 600): (i) *Master data* identify, classify, or characterise products and resources focusing on characteristics that do not regularly change, (ii) *status data* describes the current state of an instance of a product, process, or resource, (iii) *transaction data* characterise events at the time they occur, and (iv) *operational plans* contain information about an organisations planned master data, statuses and events. These data types and their relationship with time are symbolically shown in Figure 2-17.

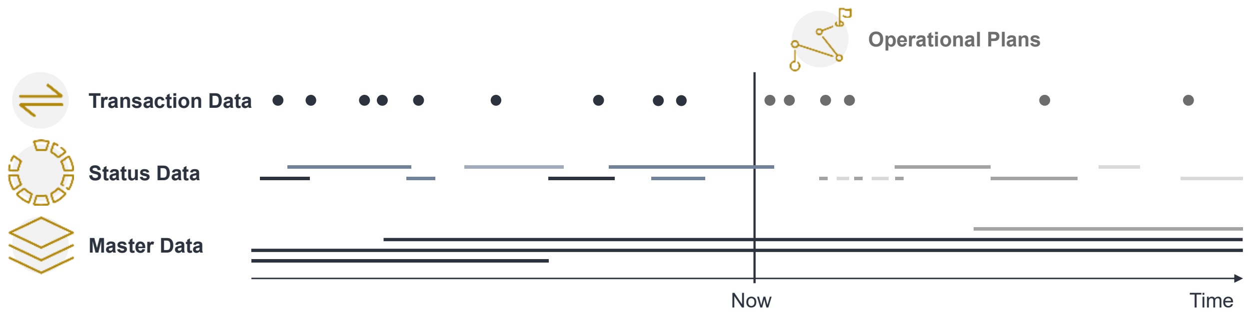

Figure 2-17: Data Types in Production Systems and their Relationship with Time

Furthermore, data can be distinguished by the type of attribute into *categorical*[10] and *quantitative*. Categorical data can be (i) *binary*, where only two states are allowed, (ii) *nominal*, where each distinct value designates a non-ordered category, and (iii) *ordinal*, where each value designates a category in ranked order. Quantitative data is either *discrete* or *continuous* and may be organised on interval or ratio scales. (Han, & Kamber et al., 2011, p. 40ff; Klein & Scholl, 2012, pp. 34–37; Stevens, 1946)

[10] Also referred to as qualitative.

As data are used as a representation of the real world in DSS, the representation quality is crucial (Price & Shanks, 2008, p. 68). Based on Hazen et al. (2014, p. 74), the quality of data may be measured in terms of *accuracy*, *timeliness*, *consistency,* and *completeness*. For each, fitting measurement definitions are available (Blake & Mangiameli, 2011, pp. 4–6; Hazen, & Boone et al., 2014, p. 74). Furthermore, the *believability*, i.e. trustworthiness of data and its *interpretability,* are important characteristics (Han, & Pei et al., 2023, p. 56). Data quality characteristics can also be organised in terms of syntactic, semantic, and pragmatic criteria (Price & Shanks, 2008, pp. 70–73). These six dimensions of data quality that this work will consider are depicted in Figure 2-18.

Figure 2-18: Dimensions of Data Quality

A core challenge when using quantitative models for PNC tasks is the acquisition of data. As discussed in Section 2.1, GPNs are shaped by various functions, and relevant data is organised accordingly. To extract knowledge from data, the knowledge discovery in data (KDD) process shown in Figure 2-19 is used (Han, & Pei et al., 2023, p. 2). It starts with one or multiple data sources and progresses with (i) *data preparation*, consisting of (a) *data cleaning*, (b) *integration*, (c) *transformation*, and (d) *selection*, (ii) *data mining*, (iii) *pattern/model evaluation*, and (iv) *knowledge presentation* (Han, & Pei et al., 2023, pp. 2–3). Depending on the specifics of the data and the demands placed on it, several methods can be applied to each step in the KDD process.

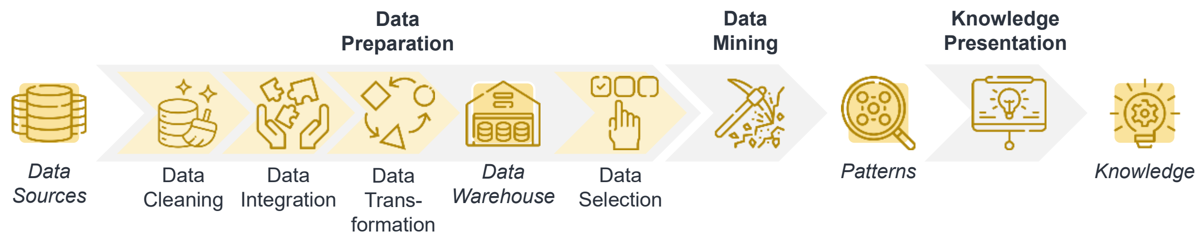

Figure 2-19: Knowledge Discovery in Data Process According to Han et al. (2023)

Before the KDD process can be applied, relevant data sources must be identified. While this task is relatively simple for data stored in one of the internal databases, which are discussed in the next sections, it may be more complex in other cases. In some cases, process mining techniques may be applied to structure transaction data in the form of a process. External data not accessible via an application programming interface (API) can be accessed using web crawlers and text mining. Product tracking refers to the comprehensive capture and storage of a product's status and transaction data throughout its lifecycle, which can also be utilised in GPN models. Finally, it may be necessary to collect additional data through interviews or manual measurements and to establish business processes that enforce adequate data capture.

2.3.2 Databases & Data Models

A database is "a […] repository of data that can be used simultaneously by many […] users" (Connolly & Begg, 2015, p. 15). DBs store data, including descriptions and logical relationships, while minimising duplication. DBs trace back to the Entity Relationship Model, first introduced by Chen (1976), which represents the real world through entities and relationships, both of which have attributes (Angele, & Kifer et al., 2009, p. 45). Most types of DBs use a schema or *data model* (DM) to define the structure that data needs to adhere to. The strictness and structure of those DMs vary depending on the type of DB used.

Several types of DBs exist and are used for different purposes. *Relational DBs* are the most common type. They are effective at storing structured data and can be accessed using the common *Structured Query Language* (SQL), which is based on relational algebra (Eembley, 2009, p. 2374). Several other DB types exist, which are often referred to as NoSQL DBs. They offer reduced structural rigidity or are optimised for specific applications. *Column-oriented DBs* store and access data by attribute instead of by element and are particularly efficient for operations across a large number of elements and a limited number of attributes. *Object-oriented DBs* store data as instantiations of classes of objects adhering to a similar structure as object-oriented programming (Urban & Dietrich, 2009, p. 1929). They provide users with additional flexibility and are particularly effective when used in combination with complex object-oriented programs. *Graph DBs* organise data as a graph, allowing for a very flexible data structure. Though these NoSQL DBs have specific advantages, they lack the broad support relational DBs have across a range of applications and IT systems.

Two noteworthy aspects of DBs are the realisation of temporal validity and the management of access restrictions. *Temporal DBs* are an extension of the previously discussed DB types, which store both historical and current data and also record alterations to the DB, in contrast to other DBs, where only currently valid data can be stored (Date, & Lorentzos et al., 2014, 61ff.). *Access control mechanisms* protect DBs against unauthorised access. The interaction with the users can categorise them into (i) discretionary, (ii) mandatory, and (iii) role-based access (Samarati & Vimercati, 2001, p. 139). Another categorisation focuses on the interaction with the contents of the DB, differentiating (i) table-based, (ii) view-based, and (iii) content-based access (Al-Haj & Aziz, 2019, p. 2; Bertino & Sandhu, 2005, p. 5).

In addition to the DB itself, different systems are used to organise the organisational interaction with the data, most notably *data warehouses* (DWH) and *data lakes (Han, & Pei et al., 2023, pp. 85–96)*. DWHs are employed to organise data from multiple sources for analytical purposes. They combine a DB with extract, transform, and load functionality (Han, & Pei et al., 2023, pp. 86–87). Whereas DWHs rely on a structured approach to combine data from multiple sources, data lakes collect and store data from a range of sources without organising them (Han, & Pei et al., 2023, p. 93).

2.3.3 Information Systems in Production

As previous sections have shown, PNC tasks require a substantial amount of data describing the organisation. This data is typically captured in the organisation's main information systems, which serve as data sources for DSS used in PNC tasks. *Information systems* (IS) are sociotechnical systems composed of human and machine components that support the collection, structuring, processing, provision, communication and use of data, information, and knowledge (Krcmar, 2015, p. 22). In industrial practice, the term is often used to refer to administration systems used to store and process large volumes of data in organisations (Schmidt, & Meier et al., 2014, pp. 283ff.). The integration of ISs in enterprises is standardised by the DIN German Institute for Standardization (2013). The following section describes the most relevant ISs for PNC tasks.

Modern *Enterprise Resource Planning* (ERP) systems are tools for comprehensive planning, coordination, and management of companywide tasks (Nettsträter, & Geißen et al., 2015, p. 3). They offer functionality for finance, accounting, controlling, manufacturing, logistics, sales, procurement, customer service, and research and development (Gronau, 2021, pp. 6–7; Nettsträter, & Geißen et al., 2015, p. 3). The defining characteristic of ERP systems is the integration of multiple functions, tasks and data within one single IS (Gronau, 2021, p. 4). A wide variety of ERP system configurations and integrations is possible, varying by industry and organisation (Gronau, 2021, p. 10). ERP systems typically extend beyond the simple provision and storage of data, instead integrating applications for a multitude of organisational user groups (Gronau, 2021, pp. 27–28). Typically, ERP systems are well connected to other internal systems, such as manufacturing execution systems, customer relationship management systems, and product data management systems, but also other organisations' ERP systems, usually through the EDIFACT protocol (Gronau, 2021, p. 39).

Supply Chain Management (SCM) systems extend the information scope across the supply chain, typically involving multiple companies. *Advanced Planning Systems* (APS) are an extension of ERP or SCM systems, which allow integrated planning across multiple companies within a supply chain (Stadtler, 2004).

Manufacturing Execution Systems (MES) collect, process, and store information from sensors, programmable controllers, and monitoring and control systems (Kletti & Deisenroth, 2018, p. 1). The data are aggregated and used to control production systems and schedule activities close to the shopfloor (Kletti & Deisenroth, 2018, p. 1). MES are primarily relevant for PNC tasks, information providers for recorded data on processing operations.

Product Data Management (PDM) systems store and relate production specifications, typically created using *Computer-Aided Design* (CAD) systems (Schmidt, & Meier et al., 2014, pp. 285–286). The logical successors, *Product Lifecycle Management* (PLM) systems, include product data beyond the product development and design phase and thereby enable cross-company interdisciplinary engineering solutions (Sendler, 2009, pp. 5-9,14-15). *Computer-Aided Quality* (CAQ) systems support various quality management processes in enterprises (Refflinghaus, & Böhme et al., 2024, pp. 9–10). *Customer Relationship Management* (CRM) systems structure the relations with customers by consolidating their information and integrating service, order processing, sales and marketing (Kumar & Reinartz, 2018, pp. 11–14). In analogy, *Supplier Relationship*

Management (SRM) systems are used to support the procurement of goods and services through internet-based interfaces (Appelfeller & Buchholz, 2011, pp. 18–19).

2.4 Digital Twins

In the following, the previously indicated concept of *Digital Twins* (DT) is introduced and contextualised within an increasingly digitised production environment. *Cyber-physical Production Systems* (CPPS) and *Industry 4.0* are discussed in 2.4.1 as the setting where DTs are emerging. 2.4.2 introduces the term digital twin and the related concepts of digital master and shadow and defines their interpretation within this work.

2.4.1 Cyber-Physical Production Systems

In recent years, much attention has been given to cyber-physical systems (CPS) and CPPSs. CPPSs embody the modern understanding of production systems as consisting of physical, i.e. mechanical, electrical, and chemical and computational entities, which continuously interact (Becker & Stern, 2016, p. 405). The so-called Fourth Industrial Revolution has partly driven this understanding. The central promise of creating CPPS is to address the complexity of production systems while minimising the necessary employee effort, thereby enabling more efficient production (Nyhuis, & Hübner et al., 2017, pp. 33–34). By capturing accurate data from the production system and providing it quickly as a service to intelligent control systems Ismail and Kastner (2017, p. 371), decisions in production can be made more quickly, with a broader consideration of context, higher transparency, and improved results. In these control systems, the concept of models, i.e., simplified representations, has remained central. As the next section discusses, it is augmented with current data from the system it represents to form digital twins.

2.4.2 Digital Shadows, Digital Masters, and Digital Twins

The term *digital twin* (DT) has gained popularity in both academic and industrial discourse. It appears to have originated in the early 2000s, when it was used to refer to comprehensive quantitative models of NASA's rockets, enriched with live data from real objects. Since then, the idea has been applied in various contexts, and scholars have discussed what constitutes a DT. The main distinctions have arisen regarding the issues of model comprehensiveness and the connectivity of real systems and models. Some have argued that a DT should effectively mirror every characteristic of a real system. However, this contradicts previously established knowledge on models as purposeful simplifications (c.f. 2.2.3.2). Recent contributions instead advocate for suitable levels of comprehensiveness, tailored applications and model fidelity (Jones, & Snider et al., 2020, pp. 46–47). However, many understand the digital twin as a unifying entity for multiple different models built for different purposes, all of which contribute to a comprehensive description of the system's behaviour.

A popular definition for DTs is provided by Kritzinger et al. (2018), who distinguish digital masters, digital shadows, and DTs by the level of connectivity with the real system. By their definition, digital masters are quantitative models only connected to real systems through human interaction, digital shadows are models with a unidirectional automatic connection feeding data from a real system to a model, and DTs are models with a bidirectional data connection (Kritzinger, & Karner et al., 2018, p. 1017).

However, this definition does not include many systems with a mandatory interface between model results and their real-life realisations, for example, in product design and non-short-term production management. Furthermore, it does not specify the scope of the automatic connectivity. A competing definition is offered by Stark et al. (2017, p. 169), characterising a digital twin as "[…] the digital representation of a unique asset (product, machine, service, product service system or other intangible asset), that comprises its properties, condition and behaviour by means of models, information and data." They specify that a digital twin is an instantiation of a *digital master* through the provision of asset data, coined *digital shadow* (DS) (Schuh, & Salmen et al., 2017, p. 10; Stark, & Kind et al., 2017, p. 170). Other authors also use similar definitions in production system design and management.

Adapting Stark et al.'s (2017) definition, a DT shall be understood in this work as an *executable digital model or model complex of a system continuously and automatically synchronised with said system*. The concept is illustrated in Figure 2-20, which shows the relationship between a real system and one or more models of it, transformed into a DT by automating the parametrisation.

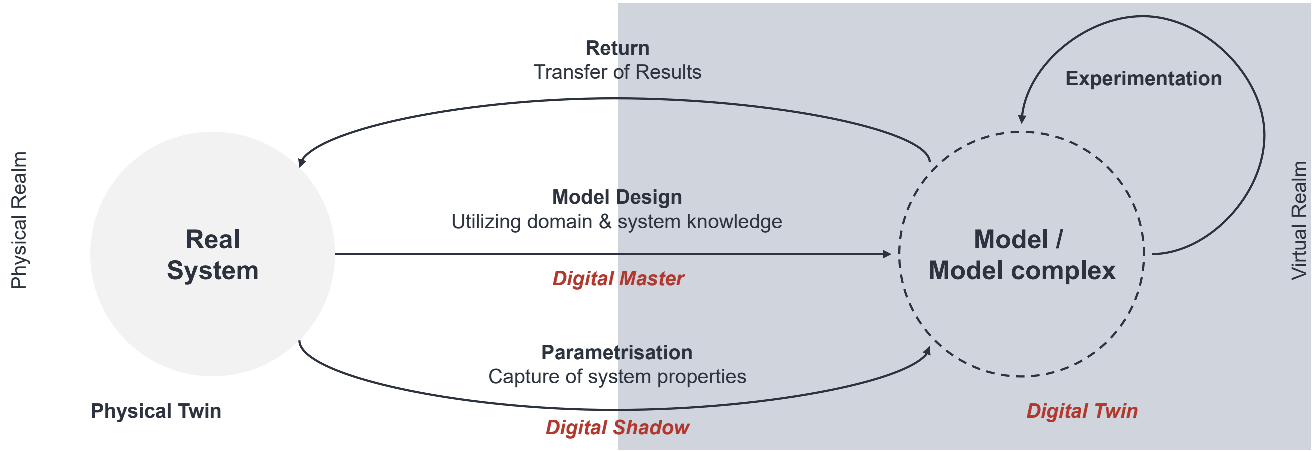

Figure 2-20: Relations between Digital Masters, Digital Shadows, and Digital Twins

A central component of DTs is the automatic generation of models from an initial digital master. Whereas manual model generation from a set of data can rely on human abilities to abstract and specify the available data under contextual consideration, automatic generation requires a comprehensive formalisation of the necessary transformations into an algorithmic form[11]. This requires a definition of all characteristics of a model that should be updated as parameters. The associated difficulty of the parametrisation varies depending on the relevant characteristics and the type of model.

[11] Recent advances in machine learning have softened this requirement, as they allow for the context-sensitive transformation of data. This may be an avenue to retain the creativity and flexibility of human model creation while reducing the time required to specify model generators. However, even though some initial applications are apparent, this shall not be within the scope of this work.

3 State of the Art

Building upon the practically motivated research objective introduced in Chapter 1 and the fundamentals presented in Chapter 2, this chapter critically examines state-of-the-art research. Section 3.1 outlines criteria for evaluating existing research approaches, which are motivated by the research objective. Section 3.2 then presents and discusses relevant research, before 3.3 offers a summary of the remaining research deficit and the subsequent need for action, expressed as research questions that this work addresses.

3.1 Evaluation Criteria

Based on the overall objective of this work, four requirement categories are defined, with fourteen criteria towards a framework for multi-purpose model-based DSS in PNC. These criteria are used to evaluate the existing approaches introduced in section 3.2 and to infer the research deficit in section 3.3:

(1) **Decision support:** For successful decision support in the described heterogeneous decision situations, the systematic selection and design of fitting models are necessary (Chandra & Grabis, 2016; Wu, & Yue et al., 2016)**.** For this purpose, **different decision situations** in **PNC** must be **investigated** and **characterised** (criterion C1). To form-fit DSSs, a broad **range of methods** supporting the decision process must be examined, characterised, and embedded in a general decision-making model (C2). Finally, a process needs to be designed that structures the design process of such DSSs and aids in the **systematic selection and design** of **suitable method elements** as a guided conceptual modelling approach (C3).

(2) **Model architecture:** The ability to quickly support various network configuration decisions is contingent on a fitting model architecture for the DSS (Volling, & Matzke et al., 2013). This architecture is the basis for a DSS capable of many GPN configuration decisions. First, this architecture must define an **adaptable data model** for GPN modelling so that the integration of data sources is decoupled from specific DSS and provided as a service (C4). Second, the architecture must **support PNC decisions** with various objectives, time horizons, and decision situations (C5). Third, to utilise resources as efficiently as possible, the model architecture should include the possibility for application models to utilise **additional functionalities**, such as accessing past system states, calibrating model parameters, and exchanging

information intelligently between different models (C6). These features could also help mitigate the difficulties in validating configuration models (Chandra & Grabis, 2016). Finally, the architecture should support the **parameter-based generation** of new **model instances** based on existing application models (C7).

(3) **Data acquisition:** To ensure the model accuracy and enable the continuous comparison with the GPN, requires systematic and comprehensive data acquisition (Srai, & Settanni et al., 2019). As relevant data for production network decisions is stored in diverse data sources, such as ERP systems, MES, CRM Solutions, PDM, and expert systems, integrating these different sources is critical for updating the information on the network. Thus, **suitable data sources** must be identified, and a procedure for their selection and inclusion into the DSS needs to be described (C8). Suitable **acquisition strategies** must be implemented to integrate and transform the data according to the demands (C9). Furthermore, as data quality problems are common in GPN modelling (Hazen, & Boone et al., 2014), the framework should include a procedure and methods for **data preprocessing** (C10).

(4) **Organisational integration:** Impactful decision support should have a robust organisational integration, ensuring that tools are used to their maximum potential and modelling results and insights are shared throughout the company (S. Liu, & Duffy et al., 2010). Thus, the framework must adapt to the **specific requirements** of the employing company, even beyond the individual decision situations (C11). The models should be usable in different **application types** defined within the framework (C12). To guide companies in developing their multi-purpose DSS and its components, they should be aided in determining the **effort and benefits** associated with these components (C13). Finally, a methodology for developing a company-specific **implementation procedure** for an adaptable DSS to support GPN configuration should be provided (C14).

3.2 Existing Approaches

The following sections examine existing approaches, at least partially addressing the research objective raised in Chapter 1. These approaches can be structured into five groups. Group I includes approaches that contribute to a particular model providing decision support in a limited range of PNC tasks (3.2.1). Group II approaches provide a decision process for PNC tasks supported by one or more models (3.2.2). Group III offers general DSSs for PNC tasks (3.2.3). Group IV contributions concentrate on providing decision support through live data (3.2.4). Finally, Group V proposes DSSs that support non-configuration tasks in GPNs (3.2.5). Each approach is described briefly and compared to the requirements raised in 3.1.

3.2.1 Specific Decision Support Models in GPN (I)

Numerous specific decision support models for GPN and SC configuration focus on one type of decision at a particular company. These approaches have been described in several review papers, namely Melo et al. (2009), Peidro et al. (2009), Volling et al. (2013), and Govindan et al. (2017). The following section examines the most noteworthy approaches from this group in relation to the objectives of this work.

Fleischmann et al. (2006) propose an MIP approach for strategic network planning for a German automotive manufacturer. The model's dedicated task is to plan the allocation of products to sites over a 12-year time horizon. The model integrates factors specific to the strategic allocation task, such as net present value investment calculation, including international tax considerations, and flexibility. The model can be applied to multiple decision instances, but it does not account for problems that are structured differently. Integration into a standard data structure is not explicitly considered, and although an estimation of substantial benefits is provided, they are not systematically deduced.

A modelling framework for mass customisation SC’s is provided by Labarthe et al. (2007), focusing on multi-agent simulation. The approach proposes a modelling approach derived from Frantz (1995) and adapted to create an agent-based simulation while considering different stakeholders in the modelling process. The connection of resulting models with advanced planning systems is discussed. The framework is used to develop a model for the supply chain planning of a golf club manufacturer.

Bihlmaier et al. (2009) present a two-stage stochastic MIP for strategic product allocation and investment planning under consideration of workforce planning. The problem is solved using a proprietary Benders decomposition. The approach is demonstrated using an example from the automotive industry. Though some tactical aspects are considered, their applicability to different types of tasks is limited. Specifics regarding data integration and organisational integration are not discussed.

Another case of strategic network planning in the automotive industry is proposed by Kauder and Meyr (2009). Their MIP minimises the net present value of the network while considering flexibility using chaining constraints of plants and products.

Nickel et al. (2012) propose a multistage stochastic MILP for supply network design considering uncertainty, budget restraints, and service levels. The model is primarily focused on distribution decisions.

Chien et al. (2013) use a two-stage stochastic MILP for production technology investment at existing sites and cross-site capacity adaptation in the semiconductor industry. The model is relatively specific to the application.

A very comprehensive MILP for strategic supply chain design in the aerospace industry is presented by Tang et al. (2013). The model encompasses internal processes and capacities at various sites, as well as suppliers, within a complex, multilevel production process. It proposes the number and location of production sites, as well as their technological capabilities and capacities. Furthermore, supplier selection and transportation are considered. The integration into a DSS is not discussed, and only NPV is considered an objective.

By contrast, Lanza and Moser (2014) propose a dynamic, stochastic multi-objective optimisation model for production networks, considering costs, delivery time, quality, flexibility, customer proximity and coordination effort, as well as multidimensional uncertainty considered through non-recourse optimisation. The approach is tested at a railway component manufacturer. Again, the implications of integrating the model into the company's planning processes and data infrastructure remain undiscussed.

Mariel and Minner (2015) introduce an MIP to adjust production capacity, considering duties and duty drawbacks in multi-stage, multi-period production. The approach is tested in the example of truck production, along with several different scenarios.

Ziegler et al. (2019) showcase using an MILP as decision support in a machine tool manufacturer's strategic network configuration. The approach discusses integrating the tool into the broader planning process, which includes multiple iterations and the creation of several scenarios. The authors also state that the data-gathering effort was the greatest barrier to the more frequent use of such models.

Another MILP is used by Hochdörffer et al. (2022) to determine the product variant allocation and resource and technology assignment, optimising costs. They employ comprehensive post-optimality analysis to determine shadow prices and slack variables, identifying promising avenues for adapting existing restrictions and addressing excess capacity. The approach is tested in a GPN in the aviation sector.

Klenk et al. (2023) present a MODM problem for product allocation and network configuration in multi-product, multi-stage production, using lexicographic ordering and MILP with integrated post-optimality analysis. The model integrates flexibility and reconfigurability as constraints and optimises total landed costs and customer proximity. The model is tested on the network of a producer of customised machines. While different applications of the model are briefly discussed, the full integration of the model into a company's planning process and data structure is not explored.

The presented approaches are only an excerpt of existing approaches to broader configuration problems. The presented excerpt illustrates the diverse planning problems with various objectives, company characteristics, and corresponding methods. While some approaches provide some flexibility regarding the use of models for different tasks (Hochdörffer, & Klenk et al., 2022; Klenk, & Kerndl et al., 2023; Lanza & Moser, 2014; Tang, & Goetschalckx et al., 2013), this flexibility is limited. Moreover, the issue of data integration, while highlighted by some authors (Hochdörffer, & Klenk et al., 2022, p. 2183; Ziegler, & Seifried et al., 2019, p. 224), is not examined explicitly. Finally, the approaches presented above focus primarily on the used model, rather than on the underlying decision process. In the following subsection, approaches specifically focusing on that process are presented.

3.2.2 Process-based Decision-Making Approaches (II)

Heinz (2006) describes a process and methods for network master planning, used to allocate production orders to production lines in GPN. The proposed process is very specific to the problem, but several methods, including genetic algorithms and linear programming, are proposed, embedded in the process, and tested. The approach considers the examined problem holistically but foregoes other PNC tasks. Although the company's data sources are considered, a generalizable method for data acquisition is lacking. However, the approach considers the specific requirements of the company and carefully integrates different types of problems. This part is also particular to the examined problem.

Meyer and Jacob (2008) illustrate a holistic process for long-term PNC decisions, using an unspecified optimisation model. The process is highly iterative, relying on discovering constraints through workshops and optimisation results. They discuss the benefits and drawbacks of different modelling methods (Meyer, 2008, 112–139). Adaptations to the process are discussed for the specific task and the examined company. Data acquisition is primarily left to the examined organisation, though some suitable sources are considered. Regarding organisational integration, the focus is on the rules by which companies decide when to apply the process and which variant.

Chaabane et al. (2010) describe a two-phase MCDM approach for supply chain management decisions. The first phase utilises AHP to evaluate SC configurations in terms of delivery reliability, flexibility and responsiveness, costs, and bound capital, whereas the second optimises the assignment of stocks using dynamic programming. Although the approach incorporates multiple methods tailored for different tasks, it is limited to a specific subset of tasks and is not generally applicable. The approach does not contribute to a fitting architecture for an integrated DSS or the necessary data acquisition.

A procedural approach for MCDM in PNC, considering uncertainty, is proposed by Lanza and Ude (2010). The approach first determines the configuration deterministically using PROMETHEE, factoring in both qualitative and quantitative criteria calculated through a discrete event simulation (DES). Then, a Monte Carlo simulation is used to create scenarios in the DES, and a sensitivity analysis in PROMETHEE is performed to assess the robustness of the chosen configurations. The approach applies to a limited number of different tasks in PNC as it incorporates a range of criteria and methods. It does, however, not contribute to data acquisition, and only minimal attention is given to organisational integration.

Hochdörffer et al. (2018) propose a five-stage planning process supported by an MILP, a non-linear model, and three successive integer linear programming (ILP) models that start at PNC decisions, incorporate SC configuration, and end with local order scheduling. The approach uses different criteria at each successive planning step. Overall, the approach covers PNC tasks quite comprehensively and utilises suitable models for various tasks, although the selection of models remains somewhat limited. Data acquisition and organisational integration are considered to a very limited extent, although the involvement of customers is included as part of the planning process.

Another process-focused approach is proposed by Sager (2018), who integrates a multi-objective MILP into an iterative decision-making process that features multiple reprioritisations of the objective system and rounds of data acquisition. They utilise both configurational and operational PNC decision variables, considering objectives such as cost, delivery time, delivery reliability, and remanence costs. The approach features a comprehensive assessment of decision-making needs and can be tailored to meet the specific requirements of the decision process. However, the approach remains tied to one particular model type and does not consider how it should be implemented in an organisation in detail.

Reich et al. (2019) introduce a process that first uses an AHP to determine the desirability of different production sites and then integrates that score into an MILP as an epsilon constraint that is gradually relaxed to create a Pareto-front. This approach can elegantly incorporate several qualitative metrics and company-specific assessments for the different sites but is limited in its application to other tasks and does not contribute to data acquisition or other aspects of organisational integration.

Gützlaff (2022) proposes a decision process for continuous PNC that uses stochastic cost calculation. The approach focuses explicitly on standardising the decision alternatives and providing DMC with relevant information to make an informed decision. It also considers the role of information uncertainty and availability, though it does not implement them in a DM. The integration of the process into the organisation and the implementation of the overall process are discussed.

Auberger (2022) describes a three-step methodology for PNC. After an initial descriptive phase that determines the characteristics of the decision situation, they use DES to find promising measures and evaluate them. Depending on the decision situation, this explorative phase is performed with DES and DoE, or meta-model-based optimisation is used for the multi-objective problem. Finally, a fitting MADM method is chosen to decide between promising options. The approach is developed during its application in three case studies in different industries. The author demonstrates the approach's potential to adequately cover various PNC tasks and adapt the methodology to the decision situation. However, the selection of fitting methods remains primarily determined by the model developer's expertise. Although the modelling is comprehensive, a common data structure is missing, and additional functionality is only discussed in relation to the specific chosen model. Data acquisition is acknowledged as an essential step but is not specified further. The approach considers the requirements of different companies but does not account for the value provided by implementing the DSS. Generally, the approach is not focused on providing a DSS, which may be used for multiple decisions, but rather on structuring one particular decision process.

A supply chain capacity planning process is designed by Oger et al. (2022). The process follows a three-step structure: alternative generation, assessment, and decision. Different scenarios are considered in the process. The approach proposes using predictive models that fit all alternatives and scenarios to plan but remains vague on the selection. The decision-making step is mainly aided by increased transparency on alternatives through dashboards. The approach proposes using a standard DM and some data preprocessing, but the acquisition of data is not further elaborated. While the solution's benefits are discussed, the organisational integration is not considered in detail.

Welsing (2023) propose a method to evaluate the environmental impacts of PNC decisions using ϵ-constraint-based MODM with an ILP formulation of costs and environmental impacts. They provide a DM for PNC decisions and show that the method can be used on different aggregation levels and with varying decision variables. The method discusses various forms of decision-making using Pareto fronts, but this consideration remains limited. Though a DM is provided, it is not integrated with corporate information systems. The method remains primarily focused on environmental concerns.

Whereas the previous group of approaches is focused on specific models and mostly single tasks, process-based models more often consider multiple PNC tasks. They also strongly emphasise model architecture, though this remains limited to the data structure. Furthermore, aspects of organisational integration are often explicitly considered. However, data acquisition and the realisation of a model architecture suitable for multiple consecutive model applications are missing. The following section discusses approaches that explicitly provide decision support, rather than a definitive model or a methodological process. These approaches utilise one or multiple specific models, embed them into a decision process, and allow diverse user interactions.

3.2.3 DSS for Production Network Configuration (III)

One of the earliest works which may be classified as a DSS for PNC was published by Arntzen et al. (1995). They describe a MILP that a company continuously uses to make supply chain and PNC decisions. The model is utilised for various tasks, and specific adaptations are made accordingly. Data acquisition considerations are largely overlooked, and although the solution is implemented at a particular company, organisational integration is not systematically considered.

Golm and Smirnov (2000) introduce a DSS for PNC that relies on three IT modules to integrate information from local sites and a central planning office. The system focuses on assigning production technologies and production processes to different sites. It assists the central planning office in creating and evaluating network configurations based on offers submitted by local sites. Although it exhibits the hallmarks of an adaptable system with a data structure that incorporates company-specific requirements, it remains relatively limited in the types of PNC tasks it can support and does not specify data acquisition.

The DESSCOM decision support workbench, introduced by Biswas and Narahari (2004), features an adaptable structure for supply chain modelling. It uses object-oriented structure models to generate predictive or prescriptive decision-making models for different types of decisions. The problem types considered are quite broad, though mainly focused on supply chain problems and less concerned with PNC. Therefore, production capabilities are not explicitly considered. Different modelling methods are integrated, namely MILP and DES. Although data provision is mentioned, it is not elaborated upon. The discussion of organisational integration is also limited.

Bundschuh (2008) propose a model-based strategic planning approach for automotive production systems. The core of the modular approach is a dynamic deterministic MILP. The model is comprehensive, including capacity, allocation, site, personnel, material flow, and site-structure planning, considering various costs and flexibility. It allows for adaptation to different planning tasks by reducing the comprehensive optimisation model demonstrated in two exemplary case studies. Option two, which automatically generates fitting models, is explicitly integrated. However, no integration into the company's IT infrastructure is described, and the integration of the tool into the company's structure is relatively superficial.

Chandra and Grabis (2016) describe a comprehensive framework for decision support in supply chain configuration. They analyse existing academic approaches in terms of methods applied and tasks examined and develop a general SC configuration methodology. The framework includes instructions to create an ontology for a particular supply chain, develop conceptual models, and use optimisation and simulation. Approaches to integrating data from ISs and other sources are discussed as well. The approach largely forgoes domain-specific aspects of production and focuses more on logistics. Although a comprehensive architecture, including an ontology, is proposed, models are only seen as one-time decision support, and functionalities that support repeated use are omitted. The specifics of organisational integration, like different application forms and an implementation procedure for the framework, are also missing.

While the previously discussed approaches highlight the adaptability of their respective DSS or DSS frameworks to different applications, they largely omit concerns about directly integrating data sources to generate model-based DSS. The following section discusses approaches that specifically focus on this aspect.

3.2.4 Data-based Decision Support Approaches (IV)

Bergmann (2013) use the Core Manufacturing Simulation Data (CMSD) model to generate DES models of production systems automatically. The approach seeks to provide models for different simulation demands throughout a production system's lifecycle, utilising CMSD to formalise the conceptual model and extract data from ISs. While the approach considers different demands towards the model, it focuses on planning tasks at the production system level and relies solely on DES as a predictive modelling method. It features an adaptable base structure, enabling the automated generation of models. However, the consideration of suitable data sources is limited to CMSD as a standard format. While different applications and adaptations for companies are discussed, an evaluation of the benefits and effort, as well as an implementation approach, is missing.

Gölzer (2018) present a comprehensive framework for Big Data applications in production by defining different types of applications, relevant business processes, and data sources and connecting them in a catalogue. In Gölzer et al. (2015), this approach is specified for the GPN design, which is subdivided into five types. The selection of specific modelling methods for the tasks is not considered. While a comprehensive concept for the DB and data acquisition exists, details regarding organisational integration are also not in focus.

Schuh et al. (2019) propose the ‘Internet of Production’ in which data from several perspectives and their ISs are unified as multiple digital shadows (DS) of different production resources. These DSSs are then used for various applications, such as cost prognosis (Schuh, & Prote et al., 2020), performance measurement (Schuh, Gützlaff, Hast, & Quarder, 2021), or sales and resource planning (Schuh, & Schmitz et al., 2023). While several individual applications with different modelling methods are demonstrated, no unifying methodology exists to select them. The base structure and data acquisition are also only partially specified (Schuh, Gützlaff, Schmidhuber, & Maibaum, 2021). This approach is a broad concept that serves as the foundation for individual applications.

Frick et al. (2024) build on a previous literature review (Frick & Metternich, 2022) and develop a design model for DSs of value streams. The design model structures the DS into three layers: physical, virtual, and connection, in which different functionalities are realised. Several design guidelines are stipulated to describe how the DS should be designed. The DS can be used for various use cases in the value stream, but methodologically, only descriptive and diagnostic models are considered. Integrating different data sources and necessary data processing is considered in detail, and a use-case-specific relational DM is proposed. Finally, a process is proposed to find suitable application software. Additional functionality provided to applications, and a more comprehensive implementation procedure are not discussed.

The approaches in this category place less emphasis on the systematic selection of modelling methods and instead provide a data-driven foundation for DSS in PNC tasks. However, they also only partially consider the issue of apt organisational integration.

3.2.5 DSS for Coordination in GPNs and SCs (V)

Whereas approaches exist that conceptualise a DSS for network configuration, these systems are even more commonly proposed for coordinative tasks. Coordinative tasks are often more short-term and, as such, more explicitly structured.

Galasso et al. (2009) propose a framework for decision-making in SCs with uncertain demands using a rolling-horizon MILP with fixed and flexible demand ranges. The model can be adapted to different production systems. Otherwise, it is similar to the approaches presented in 3.2.1, as the data acquisition and model architecture are not considered further.

Rudberg and Thulin (2009) integrate an APS with data and customer orders and available capacity to create a weekly delivery, production, and distribution plan, resulting in a cost reduction of 15%. However, few considerations are given to model architecture, data acquisition and organisational integration beyond the typical APS interfaces.

Heilala et al. (2010) develop a DES-based DSS for coordination tasks, including data integration and automated model creation and updating. The predictive DSS is integrated with several IS, allowing users to enhance their production plans. The work includes an implementation procedure that considers specific company requirements, data discovery and integration, and a model specification for its users. However, the modelling is limited to DES and adaption to different types of problems.

Bounif and Bourahla (2013) present a DSS for SC management decisions constituted by a scheduling optimisation and a simulation model. The approach can be adapted to various planning problems. However, extended model functions, automatic model generation, data acquisition, and organisational integration are not considered in detail.

Liebler et al. (2013) discuss a DES-based DSS framework for complex production and logistics networks. The DSS is adapted to a specific use case, realising a sophisticated data structure that integrates ISs as sources. However, the selection or adaption of different modelling strategies is not formalised, and no effort-benefit consideration or implementation procedure is provided.

Vieira et al. (2019) show a simulation-based DSS for SC disruption management using a Big Data warehouse. The warehouse is connected to several data sources. The necessary data is transformed into a simulation-optimised form, lowering access duration during runtime. The model is specified for one particular purpose, and the model architecture and organisational integration are discussed in a very limited fashion.

Kunath (2020) develops a framework for DSS as DTs utilised for order management based on earlier conceptualisations (Kunath & Winkler, 2018). The framework includes several IS and data sources, an automatic model generator, a visualisation environment, and a decision-making module. Different modelling approaches are proposed depending on the considered task. However, extended model functions, data acquisition methods, preprocessing, and effort benefit considerations are not included. Furthermore, the concept is not implemented in any form.

Ivanov and Dolgui (2021) propose a digital SC twin for risk management. They introduce a data structure with several data sources and a DSS architecture with simulation and optimisation capabilities. This framework, implemented using anyLogistix, is further explicitly developed for SC stress testing (Ivanov, 2023), and different use cases are discussed (Ivanov, 2024). The approach demonstrates the applicability of data-based DSSs to multiple tasks and an adaptable base structure. However, a conceptualisation of automatic model generation is lacking. Furthermore, while data sources are considered, data acquisition and preprocessing are not discussed, and organisational integration aspects are entirely foregone.

A multilevel CPS consisting of multiple work centres, products, stations, and an overall cyber-physical logistics system is introduced by Park et al. (2021). They use asset administration shells to represent the physical assets. The system can be simulated on demand to support various ad-hoc decisions. Though multiple tasks can be supported, the approach does not explicitly focus on method selection and design for those tasks. Although the model architecture is comprehensive, data acquisition largely relies on AAS for connections, which is suitable but requires integrating each data source. The organisational integration is also only roughly considered.

Milde and Reinhart (2022) introduce an approach to automatically generate DESs of GPNs using tracking data found in IS and generalised simulation modules. Later works complement the approach focused on using process mining in GPN (Milde, & Horsthofer-Rauch et al., 2023) and the application of simulation for order processing (Milde, & Sippl et al., 2021). However, this approach is limited to a single modelling method and does not consider the organisational integration in detail.

Castañé et al. (2023) introduce the ASSISTANT tool, a multi-purpose DSS for manufacturing systems, using several modelling methods. The tool is yet to be developed as part of a European project. Still, it demonstrates the ambition to integrate data from multiple sources, structure and process them in an ontology, and utilise them with suitable modelling approaches for various tasks. However, the conceptualised approach largely forgoes aspects of organisational integration of such tools.

The approaches presented in this section are not directly applicable to PNC tasks, but they demonstrate a stronger integration of system architecture and data acquisition.

3.3 Research Deficit & Need for Action

As the previous section shows, several relevant approaches to decision support for PNC tasks exist. However, the existing literature analysis suggests that this work's research objective has not yet been adequately met. The following section discusses the remaining research deficit before Section 3.3.2 deduces this work’s research question.

3.3.1 Discussion of the Research Deficit

In Figure 3-1, the examined approaches from 3.2 are evaluated vis-à-vis the criteria from 3.1. The fulfilment of each criterion is measured on a five-point scale from not met to fully met. It is apparent that no existing approach fully satisfies all requirements.

Requirements
- ○ Not met
- ◔ Slightly met
- ◑ Partially met
- ◕ Mostly met
- ● Entirely met

			Decision Support			Model Architecture				Data Acquisition			Organisational Integration			
			C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
	Approach		Comprehensive PNC Task Representation	Comprehensive Model Type Representation	Systematic Method Design	Adaptable Base Structure	Supports Diverse PNC Tasks	Extended Model Functions	Model Generation	Identification of Suitable Data Sources	Data Acquisition Methods	Data Preprocessing Methods	Company Specifics Requirements	Diverse Application Forms	Effort-Benefit Consideration	Implementation Procedure
I	Fleischmann et al.	2006	◔	○	○	◔	◔	○	○	○	○	○	○	○	◔	○
I	Labarthe et al.	2007	◔	◔	○	◔	○	○	○	○	○	○	◑	○	○	◑
I	Bihlmaier et al.	2009	◔	○	○	○	◔	○	○	○	○	○	○	○	○	○
I	Kauder & Meyr	2009	◔	○	○	○	◔	○	○	○	○	○	○	○	○	○
I	Nickel et al.	2012	◔	○	○	○	◔	○	○	○	○	○	○	○	○	○
I	Chien et al.	2013	○	○	○	○	◔	○	○	○	○	○	◔	○	○	○
I	Tang et al.	2013	◑	○	○	○	◔	○	○	○	○	○	○	○	○	○
I	Lanza & Moser	2014	◑	○	○	◔	◔	○	○	○	○	○	◔	○	○	○
I	Mariel & Minner	2015	◔	○	○	○	◔	○	○	○	○	○	○	○	○	○
I	Ziegler et al.	2019	◔	○	○	○	◔	○	○	○	○	○	◔	◔	○	○
I	Hochdörffer et al.	2021	◑	◔	◔	◔	◑	◔	○	○	○	○	◔	◔	○	○
I	Klenk et al.	2022	◑	◔	○	○	◑	○	○	○	○	○	◔	◔	○	○
II	Heinz	2006	◔	◕	◑	○	◔	◔	◔	◔	○	○	◕	◑	◔	◕
II	Meyer & Jacob	2008	◕	◑	◑	◔	◔	○	○	◔	○	○	◑	◔	◔	◔
II	Chabane et al.	2010	◔	◔	◔	○	○	○	○	○	○	○	◔	○	○	○
II	Lanza & Ude	2010	◑	◔	◔	◔	◑	○	○	○	○	○	◑	◔	○	○
II	Hochdörffer et al.	2018	◕	◑	◑	◔	◕	◔	○	○	○	○	◔	◑	○	○
II	Sager	2018	◑	◔	◔	◑	◑	○	◔	◔	◔	◔	◑	◔	○	◔
II	Reich et al.	2019	◑	◔	◔	◔	◔	○	○	○	○	○	◑	○	○	○
II	Gützlaff	2021	◑	◔	◑	◔	◔	○	○	◔	○	◔	◔	○	○	◑
II	Auberger	2022	◑	◔	◔	◑	◕	◔	○	○	○	○	◑	◔	○	◔
II	Oger et al.	2022	◑	◑	◕	◕	◑	○	◑	◕	○	◔	◑	◔	○	◑
II	Welsing	2023	◑	◔	◔	◑	◑	○	○	○	○	○	◔	○	○	◑
III	Arntzen et al.	1995	◕	◑	◑	◔	◑	○	○	○	○	○	◑	◔	○	◑
III	Golm & Smirnov	2000	◔	◔	◔	◔	◔	◔	○	○	○	○	◔	◔	○	○
III	Biswas & Narahari	2004	◕	◕	◔	●	◕	◔	◔	○	○	○	○	○	○	◑
III	Bundschuh	2008	◕	◔	◑	◑	◑	◔	◕	○	○	○	◔	◔	○	◔
III	Chandra & Grabis	2016	◕	◕	◕	●	◕	◔	◔	◕	◔	◑	◕	◔	○	◑
IV	Bergmann et al.	2013	◔	○	○	◕	◑	○	◕	◑	◑	◔	◑	◑	○	◑
IV	Gölzer	2018	◑	○	○	◕	◑	◑	○	●	◑	◕	◔	◑	○	○
IV	Schuh et al.	2019	◑	◑	○	◔	◔	◔	◑	◑	◑	◑	◔	◑	○	◑
IV	Frick et al.	2024	◕	◑	◔	◕	◕	◔	◔	◕	◕	◑	◑	◔	○	○
V	Galasso et al.	2009	◔	◔	○	○	○	○	○	○	○	○	◑	○	○	○
V	Rudberg et al.	2009	○	○	○	○	◔	○	○	◔	○	○	◔	○	○	○
V	Heilala et al.	2010	◑	◔	○	◑	◑	○	◑	◕	◑	◑	◑	◔	○	◑
V	Bounif & Bourahla	2013	◔	◔	◔	◔	◔	○	○	○	○	○	○	◔	○	○
V	Liebler et al.	2013	◔	○	○	◑	◑	◔	◑	◕	◔	◔	◑	◔	○	○
V	Vieira et al.	2019	○	○	○	○	◔	○	◑	◑	◔	◑	○	◔	○	○
V	Kunath	2020	◑	◑	◔	◑	◑	○	◕	◑	◔	○	◑	◕	○	◔
V	Ivanov & Dolgui	2021	◑	◑	◔	◔	◑	◑	○	◕	○	○	○	○	○	○
V	Park et al.	2021	◑	◔	◔	◕	◕	◑	◕	◑	◔	◔	◔	◑	○	○
V	Milde & Reinhart	2022	○	◔	◔	◑	○	○	◕	◑	◕	◕	○	○	○	○
V	Castañé et al.	2023	◑	◑	◑	◕	◔	◕	◑	◕	◕	◕	○	◔	○	○

Figure 3-1: Assessment of Existing Approaches

As discussed in Chapter 2, PNC tasks vary widely, and suitable decision support should be adapted to the specific conditions. Of the existing approaches, most only allow for a limited variation of tasks, and few utilise different fitting modelling methods. Approaches from group III come closest to this requirement. In most approaches, the systematic matching of functions and methods is not considered or limited to a small range of options. Exceptions are the works of Oger et al. (2022) and Chandra and Grabis (2016). However, they only consider a small selection of methods or focus more on SC than PNC tasks. For this work, the contributions of Biswas and Narahari (2004) and Chandra and Grabis (2016) are used as inspiration for decision support.

A suitable model architecture that ideally supports multiple different DSS has not yet been realised in the assessed literature. Whereas the adaptability of the data structure and the comprehensiveness of GPN modelling are at least partially fulfilled by several approaches, most notably from groups III and IV, extended functions provided towards DSS have not been considered at large, except for Castañé et al. (2023). However, their work remains entirely conceptual. Automatic model generation is also not commonly provided in groups I-IV, except for Bundschuh (2008) and Bergmann (2013), but much more common in approaches from group V, which require faster model deployments.

The acquisition of data and related concerns are mostly ignored by groups I-III, but promising approaches to the topic are found in group IV, specifically in Gölzer (2018) and Frick et al. (2024). This topic has also received comparatively closer attention in Group V, possibly due to a greater reliance on operational data in coordinative decisions.

Organisational integration has been given the least attention in the extant literature[12]. Many approaches allow the adaption to the specifics of a company, most notably by Heinz (2006) and Chandra and Grabis (2016). However, most existing works only contemplate a limited selection of model applications, except for Kunath (2020). Additionally, the consideration of effort-to-benefit ratios in model-based decision support for PNC tasks is almost entirely absent. By contrast, the implementation of the solutions is at least partially addressed by many approaches from group II-IV.

[12] This is particularly evident when considering the fulfilment distribution across all groups. Data acquisition, which has also received limited consideration, has been addressed to a greater degree by Groups IV and V.

3.3.2 Research Questions

Following the previous discussion, the research question (RQ) is derived. Motivated by the need for an organisationally integrated approach to PNC decision support that is so far only partially fulfilled in literature, the RQ is:

How can DSSs for the configuration of GPN be realised efficiently, requiring reduced efforts for each decision and thus enabling faster and better decision-making?

This guiding research question is divided into four partial research questions (PRQ). As discussed above, the diversity of PNC tasks is addressed by various approaches. However, knowledge of the design of fitting DSS is limited. Thus, PRQ 1 follows:

PRQ 1: How should suitable models be selected and designed for decision support in GPN configuration tasks?

The discussion showed that the realisation of synergies while maintaining the adaptability of the DSSs is crucial. However, such synergy has not yet been demonstrated for DSSs of PNC tasks. Therefore, PRQ 2 is:

PRQ 2: How can such DSSs be structured in an expandable form so that many different problems can be addressed?

Data acquisition is only discussed in a few approaches, focusing more on direct shop floor integration or the connection to a single IS. The nuanced and effort-considered acquisition has not yet been addressed. Consequently, PRQ 3 is:

PRQ 3: How can the data acquisition for DSSs for the configuration of GPN be realised with low effort and suitable automation?

Finally, integrating the DSS successfully into organisations while considering their objectives and incentives remains challenging. PRQ 4 captures this challenge:

PRQ 4: How can such systems be integrated into organisations to optimise their decision-making speed and quality?

4 A Digital Twin for Production Network Configuration

This chapter develops a digital twin framework for PNC to address the PRQs using the research approach introduced in 1.3. First, Section 4.1 provides an overview of the developed approach. Section 4.2 introduces a methodology for developing suitable DSS for PNC tasks. These DSS are embedded in a shared DT architecture presented in Section 5.2. A framework for data acquisition in such a DT is described in Section 4.4. Finally, Section 4.5 discusses the integration of such a DT into an organisation.

4.1 Solution Approach

This section outlines the approach to addressing the research question (RQ) posed in the previous chapter. First, the requirements for this solution are discussed in section 4.1.1. The core delimitations and assumptions are the topic of 4.1.2. Finally, 4.1.3 introduces the solution concept for the RQ and summarises the central aspects, which the following sections expand upon.

4.1.1 Formal Requirements

The herein-developed solution constitutes a design model for digital twins of global production networks, supporting configuration tasks. The solution shall satisfy the general requirements for a model postulated by Patzak (1982, pp. 309–310):

- **Empirical correctness:** The model's behaviour shall match empirical observations of the studied system as closely as possible.
- **Formal correctness:** The model shall be free of inner conflict and formal flaws.
- **Productiveness:** The model shall provide useful answers to the raised questions.
- **Practicality:** The model shall be easy to use, and results shall be easily interpretable.
- **Economical:** The effort required for model implementation and application shall be as low as possible.

4.1.2 Delimitations & Assumptions

To ensure the specificity of the developed solution and limit unproductive complexity, the following delimitations and assumptions are made in the development of a solution:

(1) The object of consideration is the production networks of a given focal company, industrially producing discrete movable products.

(2) Only PNC tasks are considered, i.e., other tasks and domains are only considered as far as they intersect with a PNC task.
(3) Specific third-party systems that serve as information sources, software development frameworks, and commercially available DSS are not considered in detail.
(4) The DSS considered are primarily intended for the design and choice phase of decision-making processes. Intelligence phase applications are only regarded as secondary use cases. Decision implementation is also not examined.

4.1.3 Conceptual Solution Approach

The RQ asks for a solution for faster decision-making through data provision. It acknowledges that PNC tasks may be too infrequent to warrant investments in data provision, but that combining multiple PNC tasks may yield a favourable solution. The design of any IT system with multiple stakeholders with distinct system requirements and preferences falls somewhere between fully standardised integrated systems and individualised, entirely fragmented systems. Higher levels of integration typically lower the necessary development effort, whereas individualised systems provide more value to each stakeholder. This work employs the principle of modularity, dividing the system into parts corresponding to the higher and lower heterogeneity of user preferences. Thereby, modules with low heterogeneity can be standardised and shared between solutions, whereas modules with high heterogeneity can be differentiated (Jain, 2008, p. 1878).

To structure the proposed solution, Power's (2002) DSS framework is used, distinguishing between the database, communication, models, and user interface as components of a DSS. The database and communication can be standardised across PNC tasks, whereas models are task specific. User interfaces are not the focus of this work. In addition, internal and external data sources can be shared across PNC tasks.

As a result, a three-layered framework for DTs of GPNs is proposed. It consists of the application layer, the base layer, the data acquisition layer, and an implementation framework. The application layer contains the task-specific DSS of the organisation, which interact with each other and correspond to the model aspect in Power's work. The applications are provided with data from the base layer, which contains a database and additional base-level functions. This layer corresponds to the communication and database components. The base layer may also be interpreted as a data warehouse, as described by Han et al. (2023, pp. 86–87), as it gathers and structures information from multiple sources for decision-makers[13]. The base layer, in turn, is synchronised with the real system through the data acquisition layer, which connects the DT to data sources. Lastly, the implementation framework encompasses a taxonomy of application usage types and a comprehensive implementation procedure. Figure 4-1 portrays this framework, which is based on a previous publication, Benfer et al. (2021), and captures the structure of the remainder of Chapter 4.

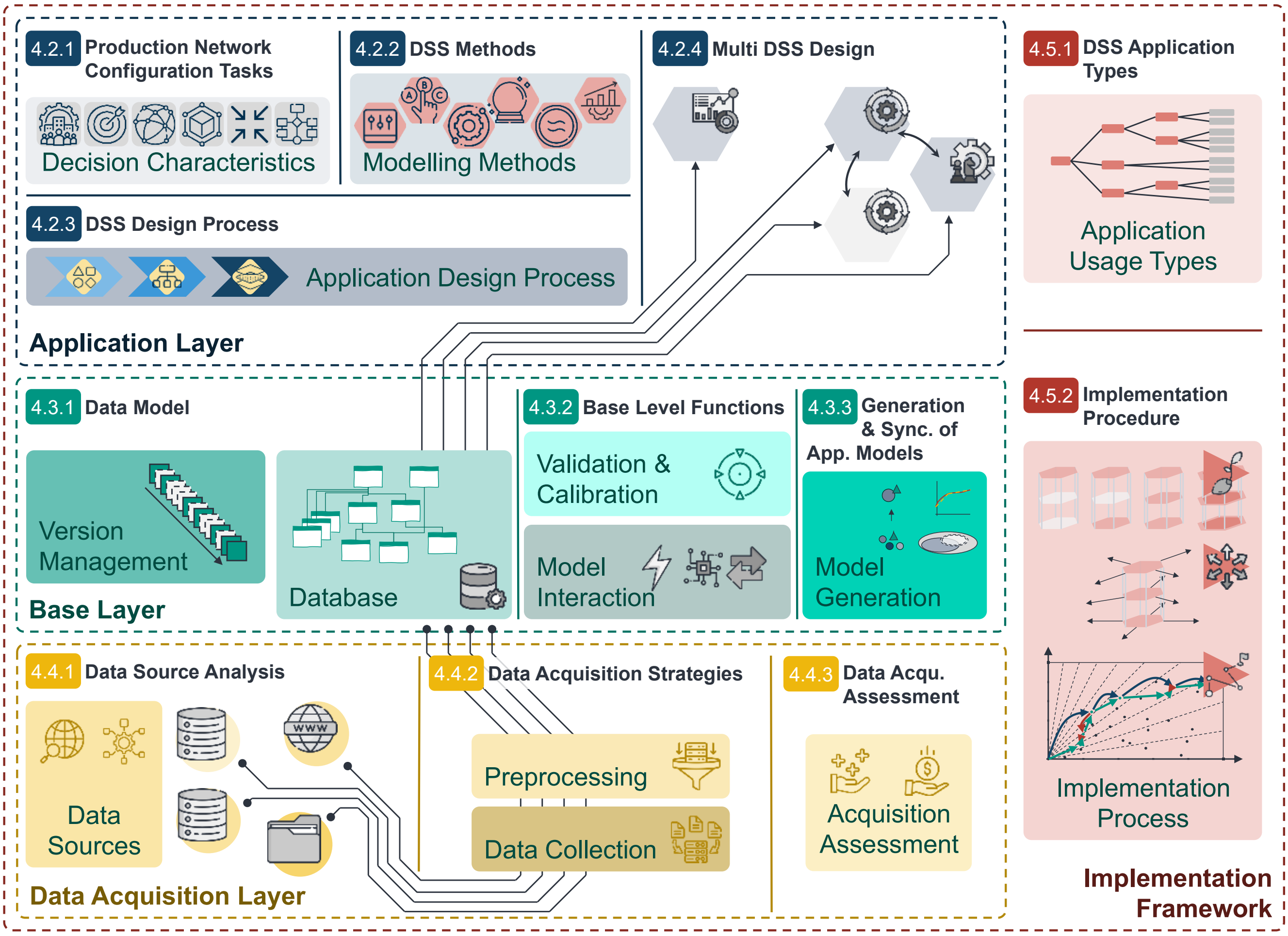

Figure 4-1: Architecture Concept for a Digital Twin of Production Networks and Structure of Chapter 4

The application layer contains models and model complexes used to support the PNC decisions, which appear to the user as their own DSS. As the previous discussion has demonstrated, designing specific DSSs is crucial for *PNC tasks*. This work considers

[13] However, the overall framework is focused on design and choice aspects of decision making, whereas DWHs are usually focused on the intelligence aspect.

DSS design from a system theory perspective, analysing the decision situation constituted by the object of the decision process, the production network, the context of that production network, the characteristics of the decision process itself, and the stakeholders, which are captured in a descriptive model. Additionally, the *modelling methods* that constitute DSSs are also categorised and described, allowing for a selection based on the decision situation. A *DSS design process* aims to identify the most suitable DSS for a given decision situation with the least effort, in terms of data acquisition, conceptual deliberations, and iterations. Finally, a descriptive model is developed to characterise the relationships between multiple interacting DSSs, extending the design process to accommodate DSS interactions and enabling structured *multi-DSS design*.

The base layer contains the synergetic internal components of the framework. The core of this base layer is a *data model*, implemented in a shared database, which utilises version management. Additionally, *base-level functions* such as validation, calibration, and model interactions support the DSS in the application layer. Finally, this work includes the systematic *generation and synchronisation of application models* for specific decision situations by enabling automated abstraction and delimitation of model instances. With these shared components, the development and iterative use of DSSs is accelerated.

Acquiring relevant and accurate data is a necessary precondition for PNC tasks. This work aims to reduce the effort required for data acquisition substantially. In a *data source analysis,* characterisations of typical data in ISs are developed. *Data acquisition strategies* are systematised to enable data collection from within and outside the organisation. A process to establish the data acquisition strategies towards the unified DB for the DT is created using methods from the KDD process. Finally, *data acquisition assessment* represents an evaluation model that considers the available quality and the requirements of existing DSS applications.

DSSs are most effective when they are well-integrated in the organisation and can support a variety of use cases. This work includes a taxonomy of such *DSS application types* and their characteristics, allowing organisations to utilise DSS effectively. Additionally, an *implementation procedure* for DSS for PNC tasks has been developed to maximise the utility provided to the organisation while considering the adoption theory. This allows organisations to dynamically prioritise their modular DT of the GPN based on the framework presented here.

4.2 Decision Support System Design

As the previous chapters discussed, the design of suitable DSSs is essential for their usefulness in industrial practice. This chapter addresses this need and, thereby, PRQ1:

How should suitable models be selected and designed for decision support in GPN configuration tasks?

The chapter begins by describing a general framework to characterise production network configuration (PNC) tasks in Section 4.2.1, followed by a systematisation of relevant constituting methods for decision support systems (DSS) in Section 4.2.2. Using those systematisations, 4.2.3 describes a general DSS design process for PNC tasks. As the previous sections focus only on individual DSS, Section 4.2.4 expands it to include dependencies and interactions between multiple DSS. Figure 4-2 provides an overview of the chapter.

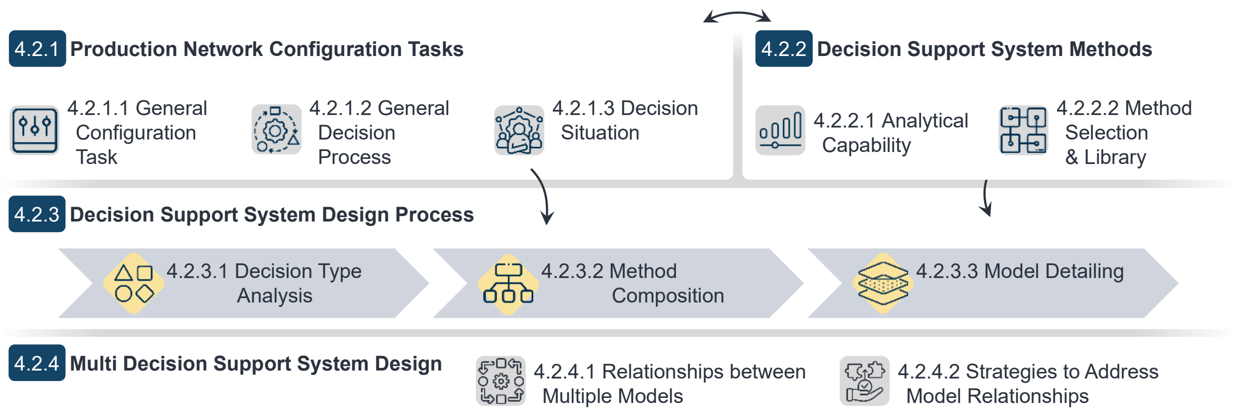

Figure 4-2: Overview of Section 4.2 – DSS Design

4.2.1 Production Network Configuration Tasks

To address PNC task heterogeneity, 4.2.1.1 unifies the variety of PNC tasks discussed in Section 2.1 in a shared framework. A general decision process applicable to all PNC decisions is designed in 4.2.1.2 to create a suitable DSS. 4.2.1.3 determines a system view model of decision situations, which informs the DSS design. The influences on the characteristics of this decision situation originating from the focal company, the pursued objectives, the domains involved in the decision, the considered elements of the production network, the shape of external influences, and the decision process used in the organisation are explored in sections 4.2.1.3.1 through 4.2.1.3.6.

4.2.1.1 General Configuration Task

This subsection defines a general reference PNC decision model. At the core of this model is production as a transformation process. Let a production process $\psi: (U_\psi, Q_\psi) \rightarrow (O_\psi) | \psi \in \Psi$ be a transition of a set of consumed inputs U_ψ and a set of capacities Q_ψ to a set of outputs O_ψ. Inputs are all items seizing to exist during the production process, whereas capacities are the consumed operating times of the set of used resources R_ψ that have the capabilities $K_\psi = \bigcup_{q \in Q_\psi} K_q$, where K_q denotes the set of capabilities necessary for a capacity $q \in Q_\psi$. This transition forms a fractal[14] system, whereby a transition ψ_1 is constituted by a set of transitions $\Psi_{\psi_1} \coloneqq \{\psi_2\}$. Then U_{ψ_1} and O_{ψ_1} can be expressed as the nonsymmetric differences between the set of all consumed inputs $U_{\Psi_{\psi_1}} \coloneqq \{U_{\psi_2} | \psi_2 \in \Psi_{\psi_1}\}$ and of all outputs $O_{\Psi_{\psi_1}} \coloneqq \{O_{\psi_2} | \psi_2 \in \Psi_{\psi_1}\}$: $U_{\psi_1} = U_{\Psi_{\psi_1}} - O_{\Psi_{\psi_1}}$ and $O_{\psi_1} = O_{\Psi_{\psi_1}} - U_{\Psi_{\psi_1}}$. The set of required capacities Q_{ψ_1} may be expressed as $Q_{\psi_1} = \bigcup_{\psi_2 \in \Psi_{\psi_1}} Q_{\psi_2}$.

Within this reference frame a production configuration $x_s^{(CON)}$ shall be defined as the specification of the resources $R_s \coloneqq \{r\}$, their capabilities K_r and capacities Q_r, which are part of the production system s. Production allocation $x_s^{(ALO)}$ shall be defined as decisions that determine the mapping of capacity demands Q_ψ for all specified transitions $\psi \in \Psi$ to capacities provided by the system Q_s as well as the mapping of required inputs U_{ψ_2} to offered interim products O_{ψ_1} for all $\psi_1, \psi_2 \in \Psi$. As allocation decisions are, in almost every case, quicker to implement than configuration decisions, configuration decisions require a longer time horizon. However, the attractiveness of a configuration is dependent on the allocation. Thus, most configuration decisions actually comprise both configuration and allocation. In cases where the demanded product quantity is not assumed to be fixed, demand definition may be a third component of configuration decisions, for example, if possible, new product variants are evaluated.

4.2.1.2 General Decision Process

As discussed in 2.2.1, numerous descriptive models of model-based decision-making processes exist. Regarding Simon's original model, this work focuses on the decision-

[14] Here, fractal refers to hierarchical systems, where subsystems are structurally similar to the supersystem.

making design and choice phase (H. A. Simon, 1960). Thus, this framework utilises the decision-making process introduced by Domschke and Scholl (2008, p. 26) and the fundamental decision problem introduced by Klein and Scholl (2012, pp. 138–140) with some adaptations motivated by the specific setting using a DSS. Specifically, the first three phases, identification, problem analysis and objective definition, are collapsed into problem definition since the type of decision is assumed to remain similar across multiple uses of the DSS. Furthermore, alternative evaluation is split into two parts, allowing for a model-based evaluation to be integrated with other non-model-based considerations in the evaluation. This adapted process is shown in Figure 4-3, consisting of (i) problem definition, (ii) scenario generation, (iii) configuration generation, (iv) predictive modelling, (v) result evaluation, and (vi) decision. It also shows which parts of this process are supported using a predictive and prescriptive model.

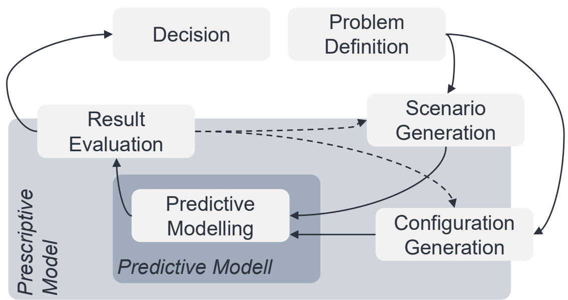

Figure 4-3: General Decision-Making Process with Models

4.2.1.2.1 Decision-Making Process Steps

The *problem definition* is the process by which a decision situation is specified such that the examined system s, its environment ϵ_s and the objectives $g \in G$ are well defined. Depending on the degree of routine in decision-making, the step can be either trivial or complex. This step is only carried out once in a strictly sequential decision process. However, real decision processes may require adjustments to the problem definition, especially when knowledge about the examined system is limited.

Scenario generation describes the formalisation of development paths, towards which the environment of the examined system could develop. This step is focussed on the part of the environment $\epsilon_s^{(IND)} \subset \epsilon_s$ which is not strongly influenced by the system itself throughout the considered time horizon $\Delta\theta^{(TH)}$ and can thus be described prior to the decision on system configuration (Klein & Scholl, 2012, p. 41).

Complete independence is often an inaccurate but necessary assumption to model the system efficiently. A typical example is the assumption that customer orders are independent of production volume allocation. The resulting scenarios $\omega \in \Omega_{\epsilon_s^{(IND)}}$ are used to evaluate the decision strategies $\boldsymbol{x}_s$.[15]

The definition of decision alternatives is encapsulated in *configuration generation*. In this step strategies $\boldsymbol{x}_s$ for decisions are designed. These strategies include configurations, expressed as state changes $\boldsymbol{x}_{s,t}^{(CON)}: \boldsymbol{y}_{s,t} \rightarrow \boldsymbol{y}_{s,t+1}$ and allocations $\boldsymbol{x}_{s,t}^{(ALO)}$ of capacity demands $\boldsymbol{q}_t^{(DEM)}$ to capacities $\boldsymbol{q}_{s,t}$ throughout the considered time periods $t \in T$. Any strategy must adhere to the system's static and dynamic state restrictions. Many configurative methods used for this process involve the iterative creation of choices and their testing using a predictive model. If the configuration is partly or fully automated, such that configurations are created based on objectives and predicted system responses, this can be considered *prescriptive modelling* instead.

Predictive modelling describes the approximation of a system's behaviour given a configurative strategy and a development scenario ω of the environment. Using a model, the behaviour is described for the previously defined objectives G. Through this process, the consequences $\boldsymbol{z}_{\boldsymbol{x}_s}$ of a selected strategy can be approximated.

Result evaluation compares different strategies based on the quantitative assessment. In conjunction with possible qualitative assessments, the degree to which the strategies satisfy the desires of the Decision-making committee (DMC) is evaluated. If the satisfaction criteria are not met, the scenario and configuration generation steps, as well as predictive modelling, are reiterated. The evaluated strategies move into the decision-selection step if the criteria are met.

The last step, *decision,* refers to the final selection of a choice, such that the specified objectives are fulfilled as well as possible.

This decision process deviates from others in that the system modelling and data gathering are not explicitly part of the process. This approach assumes that a fitting DSS, incorporating a predictive model, is available and synchronised with the system,

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[15] Any scenario for future developments only represents a discretised realisation of the future, which is comprehensively described by a probability density function (PDF). However, as PDFs can only be used in predictive and prescriptive modelling to a minimal extent, in most cases a discretisation is suitable.

providing a complete parametrisation of the current state. The design of such a DSS is the subject of the subsequent sections.

4.2.1.2.2 Decision Variable Sets

Each decision process π is concerned with a limited set of decision variables $x \in X_\pi$, which together form a strategy $\boldsymbol{x}$. While the decision directly influences these variables, any decision usually exists within a broader space of other decisions. These other decisions can be *fixed* for the decision $x \in X_\pi^{(FIX)}$, i.e. the decision has been made before the decision process π and cannot be changed. Furthermore, decisions made in a process can be *inconsequential*, $x \in X_\pi^{(INC)}$. These are decisions made in anticipation of scheduled plan revisions[16]. To distinguish the decision variable for which the outcome of π is binding, they are referred to as the *subject* of the decision $x \in X_\pi^{(SUB)}$. Formally $X_\pi^{(SUB)} \cup X_\pi^{(INC)} = X_\pi$ and $X_\pi \subset P_\pi$, where P_π denotes the set of parameters used in π.

4.2.1.3 Decision Situation

The decision situations described in existing academic work and industrial production network modelling case studies are heterogeneous. The characteristics of the decision situation impact the gestalt of the most suitable DSS. Therefore, this framework provides a comprehensive overview of decision situation properties pertaining to PNC. For this purpose, 16 decision situation characteristics (DC) of PNC decision situations are identified. The characteristics are chosen based on their impact on the overall desired analytical capability (AC) of a DSS and their influence on the choice between different methods. These characteristics are determined by properties of the PNC task, which are organised into (i) focal company, (ii) objectives, (iii) domains, (iv) production network elements, (v) external influences, and (vi) decision process characteristics, which are explored in the subsequent sections.

Table 4-1 displays the decision situation characteristics and the properties that influence them. A detailed description of the decision characteristics and their interaction with the PNC properties is given in Appendix A2.1. As Table 4-1 shows, most of the characteristics are shaped by several properties of the PNC task.

[16] A typical example is rolling horizon planning processes, where plans for later periods are created without having immediate consequences.

Table 4-1: Decision Situation Characteristics & Relevant PNC Properties

Decision Situation Characteristics		Description	Focal Company	Objectives	Domains	PNC Elements	External Influences	Process Char-acteristics
DC01	System Linearity	Degree to which linear equations can adequately describe the relevant system behaviour.	x	x	x	x	x	
DC02	Number of Deci-sion Variables	Number of distinct variables to be determined in the decision.	x	x	x	x		
DC03	System Expertise	System expertise of the DMC, specifically central DSS users.	x		x			x
DC04	Uncertainty	Degree to which the outcome of the system is impacted by and sensitive to uncertain developments.	x	x		x	x	
DC05	Decision Fre-quency	Frequency with which similar decisions are made.	x			x		x
DC06	Decision Routine	Degree to which the decision is standardised, the process is predefined, and the necessary inputs are known.	x			x		x
DC07	Development Capabilities	Capabilities of the organisation to develop DSS solutions.	x					x
DC08	Perspective Di-versity	Degree to which multiple distinct interests with different over-arching objectives have to be satisfied in the decision.	x	x	x			x
DC09	Achievable Accuracy	Grade of accuracy that can be achieved with the available data.	(x)	x		x	x	
DC10	Objective Quantifiability	Degree to which the pursued objectives can be quantified.		x				x
DC11	Data Acquisition Intensity	Amount of data necessary for the decision.	(x)	x	x	x	x	
DC12	Time Horizon	Length of time taken into consideration in the decision.	(x)		x	x		
DC13	Decision Time	Available time to make the decision.	(x)			x		x
DC14	Computing Capabilities	Available computational capabilities.	(x)					x
DC15	Desired Explainability	Degree to which the decision must be understood and explained to decision makers.	(x)					x
DC16	Model Expertise	Amount of model knowledge and understanding of the DMC.	(x)					x

4.2.1.3.1 Focal Company

The focal company and its characteristics are crucial for designing a DSS. This subsection proposes a descriptive model of the focal company that aids the design of a fitting DSS. Table 4-2 shows the most important focal company characteristics (FC) influencing the decision situation. These characteristics are derived from the literature introduced in Section 2.1. Due to the complex nature of the relations between individual characteristics of the company and decision situations and the lack of any empirically validated influence model, the influence of these characteristics on the previously introduced DC can only be described in broad general terms. Appendix A2.1 introduces mechanisms by which each FC influences the mentioned DCs. These mechanisms can be utilised when assessing the overall decision situation.

Table 4-2: Focal Company Characteristics relevant for DSS Design

Focal Company Characteristics		Description	Impacted Decision Situation Characteristics
FC01	Organisation Size	Size of the organisation in terms of turnover, employees, & sites.	DC02, DC05, DC06, DC07, DC11, DC14, DC15
FC02	Decision Centrality	Degree to which relevant decisions are centralised in the company	DC01, DC02, DC03, DC05, DC06, DC07, DC08, DC15
FC03	Market Relation	Point of product creation process orders are introduced at	DC01, DC04, DC08
FC04	Resource Share	Share of resource costs in production costs	DC02, DC04, DC12
FC05	Product Heterogeneity	Degree to which products of the organisation differ from each other	DC02, DC08, DC11
FC06	Production Lead Time	Time between the start of production and the delivery of a product	DC04, DC12
FC07	Product Stability	Time a product type is sold in the market without change	DC04, DC05, DC12
FC08	Vertical Integration	Share of value creation performed within the company	DC01, DC03, DC04, DC08, DC11
FC09	Production Volume	Number of products produced	DC01, DC02, DC11
FC10	Production Technology Stability	Degree to which production technology remains stable across generations	DC01, DC02, DC03, DC04, DC05, DC08, DC11,
FC11	Commoditisation	Degree to which sales are determined by price	DC01, DC08
FC12	Production Splits	Split of production across sites	DC01, DC02, DC08, DC11
FC13	Product Value Density	Value per volume or weight of product.	DC02, DC08
FC14	Digital Maturity	Capabilities and IT infrastructure of the organisation	DC07, DC09, DC11, DC14, DC16

4.2.1.3.2 Objectives

DSS can be used towards a multitude of ends in PNC. The objectives selected and their relative importance influence the choice of adequate modelling methods, the decisions made during the decision process, and the success of the decision. Thus, choosing the correct objectives is crucial for DSS design. For the development of task-specific DSS, a reference objective structure is developed, which includes the objectives discussed in 2.1.4.1, available specific KPIs, required PNC elements and considered domains, and quantifiability and modelling complexity. Noteworthy existing approaches using those objectives and KPIs are also considered. An overview of the objective structure is presented in Table 4-3 and the hierarchy is discussed in Appendix A2.3. In the table, the implications on decision situation characteristics are rated from very negative (--), referring to a strong reduction of the relevant dimension, to very positive (++), referring to a strong increase. Due to the complexity and limitations of knowledge, the influence on DCs cannot yet be put into a formula. Instead, each influence may be taken into account when assessing the DCs.

Table 4-3: Reference Objective Structure in Production Network Configuration

Objective Category	Objective Type	Variants	Implications on DC 01	DC 02	DC 04	DC 08	DC 09	DC 10	DC 11
Company Success	Profit	Net Present Value, Profitability, Profit Margin		+	+	+		+	+
	Viability	Likelihood of Survival, Diversity of Dependencies, Static Monetary Viability	--	++	++	++	--	-	++
	Competitive Position	Market Share, Price Position, Competitive Strength, Game-Theoretical Value	--	+	++	++	-	-	++
	Company Value	Discounted Cash Flow, Economic Value Added, Tobin's Q, Real Options Valuation	--	+	++	++	-	-	+
Operational Objectives	Costs	Static Total Costs, Net Present Costs, Equivalent Annual Costs, Unit Production Costs, Activity-Based Costing Evaluation, Risk-Adjusted Expected Costs, Emission Costs, Penalties			-	-		++	
	Utilisation	Capacity Utilisation Rate, Overall Equipment Efficiency		-	--	--	++	++	-
	Throughput	Throughput Rate, Order-to-Delivery Time, Inventory Turnover	-	+	+	+	-	++	+
Customer-related Objectives	Quality	Defect Rate, First Pass Yield		+		+	+	+	+
	Delivery	Average Delivery Time, Delivery Reliability, Delivery Lead Time Variability, Expedite Frequency	--	+	+	+	+	+	+
	Flexibility	Volume Flexibility, Sourcing Flexibility, Variant Flexibility, Delivery Flexibility	-	+	+		-	-	+
	Innovation	Time-to-Market, Product Introduction Rate	-	+	+	+	-	-	+
	Service	Service Proximity, Mean Time to Repair/Replace	-	+	-		+	-	+
Dynamic & Structural Objectives	Dynamic Capabilities	Adaptability, Internal Flexibility, Value at Risk, Robustness, Recovery Time, Resilience Loss	--	+	++		-		++
	Complexity	Network Entropy, Coordination Costs	-	+	+	+	--	-	+
	Knowledge Protection	Intellectual Property Risk, Supplier Intellectual Property Exposure, Sensitive Process Protection	+		+	+	-	-	+
ESG Objectives	Environmental Stewardship	Global Warming Potential, Water Consumption, Ecological Hazard, Biodiversity Effect, Captured Land		+	+	+	-	-	++
	Societal Responsibility	Worker Safety, Job Security, Living-Wage Coverage, Community Impact		+		+	-	-	++
	Corporate Governance	Corruption Exposure, Supplier Compliance, Regulatory Complexity		+	+	+	-	--	++

4.2.1.3.3 Domains

PNC tasks encompass a system composed of various subsystems, of which the production of goods is only one part. Each subsystem or domain follows specific rules and needs to be modelled accordingly. Furthermore, the domains are usually managed by different stakeholders inside an organisation and may pursue distinct objectives. Depending on the specific PNC tasks, domains may be more or less affected. Thus, this framework categorises relevant domains for PNC tasks and major variants of those domains, which describe different behavioural patterns. For this work, the following domains are adapted from the activities defined by Porter (2004, p. 37): (i) production, (ii) procurement and supplier management, (iii) logistics, (iv) sales, (v) customer service, (vi) product design, (vii) quality management and control, (viii) site and resource management, (ix) human resource management, and (x) strategic management. Table 4-4 shows the domains in this framework, as well as a categorisation of variants. Characteristics of the focal company and production network elements primarily determine these variants. For the inclusion of domains, a general mapping of affected DCs is not possible, as the effects are too dependent on the variant of each domain, the specifics of the inclusion in the decision process and the set of included domains as a whole. In general, however, the linearity of the system (DC01), the number of decision variables (DC02), the system expertise of the DMC (DC03), the diversity of perspectives (DC08), the intensity of data acquisition (DC11), and the time horizon to consider (DC12) are most affected. A discussion of the domains, their variants, and implications on the DCs and model design is provided in Appendix A2.4.

Table 4-4: Domains in PNC Tasks and Major Variants

Domain		Description	Variants
Primary Domains	Production	Planning, control, and operation of value-adding transformation processes.	
	Procurement & Supplier Management	Identification, selection, development and coordination of suppliers and their goods and services.	Commodity procurement, highly integrated suppliers,
	Logistics	Planning and coordinating logistic operations for sourced parts, inter-site transfers, and distribution.	External logistics services, just-in-time logistics, exceptional transports
	Sales	Customer acquisition and management, planning, acquiring, and managing orders.	Commodity sales, frame-contracting, market dominance, seller's market
	Customer Service	Management and provision of service offerings to customers.	External service, service-driven business, aftermarket production
Support Domains	Product Design	Development and design of products and components.	Configured products, engineer-to-order business
	Quality Management & Control	Management and assurance of the quality produced.	
	Site & Resource Management	Management and coordination of local infrastructure and assets.	External infrastructure management, immovable assets
	Human Resource Management	Acquisition, management, and development of personnel.	Large leasing workforce, strict worker protection laws/agreements
	Strategic Management	Strategic management and coordination, coordination of other domains	

4.2.1.3.4 Production Network Elements

GPNs consist of several element types that must be represented in production network models. Depending on the specific decision, some of those elements can be omitted. In the following, a comprehensive model of relevant elements is developed. As discussed in 4.2.1.1, the main decisions in PNC concern defining resources r and their characteristics. Therefore, the model contains several resource classes $\hat{r}$ representing different aggregation levels. Different archetypal change operations may be defined for each resource element. Aside from the resource elements, additional elements are necessary to capture demands, products and goods, processes, and policies. The change events associated with those elements are outside the scope of the configuration decision or take relatively little time.

Table 4-5 displays the PNC element library, presenting the configurable elements for PNC and their available modes of change, along with estimated change time rates for each element and mode[17]. The elements and change characteristics are based mainly on existing literature and experiences. A more detailed depiction of the change modes and relevant sources is provided in Appendix A2.5.

Table 4-5: PNC Element Library and Main Change Mode

PNC Element	Description	Change Mode	Estimated Time Range
Production Site	Sites with value-adding activities operated by the focal company.	Set-Up	2-5 Years
		Expand	1-3 Years
		Consolidate	1-3 Years
Auxiliary Site	Sites which accommodate non-value-adding functions of an organisation, such as service, sales, development, etc.	Set-Up	3-24 Months
		Consolidate	3-18 Months
Logistic Site	Sites that are used explicitly for logistical purposes, such as warehousing, transhipment, or distribution.	Set-Up	1-5 Years
		Consolidate	1-2 Years
Supplier	Supplier for parts, resources, and processing.	Select	1-12 Months
		Develop	3-24 Months
Production Technology	Type of processing characterised by a specific set of necessary expertise and characteristics.	Set-Up	0.5-5 Years
		Move	0.3-3 Years
		Consolidate	3-12 Months
Production Resource	Machines, lines, and plants.	Set-Up	1-24 Months
		Move	3-12 Months
		Adapt	0-6 Months
		Consolidate	1-12 Months
Auxiliary Capability	Capabilities associated with not directly value-creating functions like service, sales, or development.	Establish	0.5-3 Years
		Consolidate	6-18 Months
Personnel	Staff directly or indirectly associated with value creation, process expertise.	Hire	1-24 Months
		Retraining	1-12 Months
		Lay Off	0-3 Years
Tool	Production technology and product-specific appliances used to customise production resources to products.	Create	0.5-12 Months
		Move	0-3 Months
		Discard	0-3 Months
Transport Mode	Type of transport chosen on a specific route.	Set-Up	1-12 Months
		Cancel	1-6 Months
Releases & Certifications	Allowances to produce products on specific resources.	Acquire	1-12 Months
Work Time Model	Policy by which worker capacity is determined temporarily.	Change	0.5-12 Months
Set-Up	Resource configuration determines capabilities and processing times.	Change	0-1 Week

[17] The change time refers to the time from decision to manifestation when the system operates in its new, desired form. It does not include the time until an investment is refinanced. The estimations represent typical values.

The selection of considered PNC elements affects a range of DCs. As a generalisation, more long-term decisions with longer time horizons (DC12) are associated with higher uncertainty (DC04), lower decision frequency (DC05) and routine (DC06), lower achievable accuracy (DC09), higher data acquisition intensity (DC11) and longer decision times (DC13). The relations with system linearity (DC01) and the number of decision variables (DC02) are more complex and need to be considered separately[18].

4.2.1.3.5 External Influences

Several external influences act on GPN. Depending on the specific PNC task, different external influences are more or less relevant. To classify influences, this work refers to Lanza et al. (2019, p. 828), who distinguish influences from market and market development, cost factors, logistics, people and culture, legal factors, political and governmental factors, and risks and dynamics. Table 4-6 shows common external influences on PNC tasks and their effect on the DCs[19]. A more detailed discussion of these influences is given in Appendix A2.6.

Table 4-6: External Influences on PNC Tasks based on Lanza et al. (2019)

Influence Category	**Aspects**	**Influence on**				
		DC01	**DC04**	**DC09**	**DC11**	**DC13**
Market & Market Development	Changes and volatility in the number of customers, customer preferences, demand, and competition.		++	--	+	-
Cost Factors	Local costs of labour, capital, material, energy, and communication, and local productivity.	-	+	-	+	
Logistics	Transportation and inventory costs, transport lead time and frequency	--	+	-	+	--
People & Culture	Training levels, employee turnover rate, cultural preferences	-	+	-		
Legal Factors	Rule of law, knowledge protection, and corruption	-	+	-	++	
Political & Governmental Factors	Political stability, subsidies	-	++	--	+	-

The relevance of these factors varies across PNC tasks. As the consideration of factors entails adding complexity to decision-making models, an appropriate degree of consideration needs to be determined. The relevance of influences refers to the extent to which external factors can alter configurational decisions. Therefore, it consists of the

[18] The linearity is dependent on the specific elements and their variants. In very long-term decisions, the number of decision variables tends to be relatively low, corresponding to the number of system elements. For short-term decisions, the considered systems are typically more limited, resulting in a decrease in the number of decision variables. The highest number can often be found in medium-term decisions that consider several element types.

[19] As Table 4-6 indicates, stronger external influences generally move the DCs in a similar direction, but the strength of those effects differs by influence.

impact $w_{g,j}^{(OIEI)}$ these influences j have on objectives $g \in G_\pi$ and thereby decisions and the degree of variance between values of the influence within the considered system in space, $\eta_j^{(SVEI)}$, and time, $\eta_j^{(TVEI)}$. Using this logic, the relevance $w_{j,\pi}^{(EXIN)}$ of an influence $j \in J^{(EI)}$ on a specific decision process π can be described as

$$w_{j,\pi}^{(EXIN)} = \sum_{g \in G_\pi} \left(w_{g,\pi}^{(OBJ)} w_{g,j}^{(OIEI)} \right) \eta_j^{(SVEI)} \eta_j^{(TVEI)}, j \in J^{(EI)} \qquad \textit{Equation 4-1}$$

where $w_{g,\pi}^{(OBJ)}$ is the weight of an objective g in a process π. Indicators for the impact of influences and an assessment scheme for influences are provided in Appendix A2.6.

4.2.1.3.6 Decision Process

Whereas the previous sections have described the external and internal environment of the decision, its objectives and the system under consideration, this section describes the conduct of the decision itself. It is characterised by the stakeholders involved in the decision process, its duration and associated urgency, the frequency with which similar decisions are made, and the formalisation of the process. A Responsibility Assignment Matrix (RAM) can be used to describe stakeholders and their respective responsibilities. The process can be captured using Business Process Modelling Notation (BPMN). A characterisation scheme for decision processes is offered in Appendix A2.7.

The involved stakeholders can be described based on their domain and particular role in the decision process. Decisions become more deliberative when decision-making power is distributed across different company functions or resources, and the explainability of results becomes increasingly important. Decisions need to integrate more potentially conflicting objectives. A broader set of stakeholders can also improve data availability. Modelling and system expertise in the DMC, as well as decision-making support, positively affect the ability to consider uncertainty and reduce the need for simplicity.

PNC decision processes can span multiple months or be completed within a few days. Longer decision processes allow more perspectives to be integrated, thereby lowering the trade-off criticality between computational complexity and efficiency, as longer computing times become acceptable. DSS provide a higher benefit for frequent decisions, as the one-time efforts are offset. In frequent decisions, the DMC is more acquainted with the system and the process and can acquire higher expertise with the DSS.

Formal processes require a clear definition of decision criteria, thresholds and decision rules and lend themselves more to quantitative methods. Less formal processes can be more explorative and rely more on qualitative criteria.

These aspects can be mapped relatively directly to the DCs, so that an additional conversion step is not necessary.

4.2.2 DSS Methods

This section establishes the fundamental concepts and methods necessary to design model-based DSS that address the PNC tasks structured according to the previous section. The concept of *analytical capability* (AC) of different models is introduced and discussed in 4.2.2.1. Next, the methods introduced in Section 2.2.4 and Appendix A1 are structured and characterised, and dependencies between them are uncovered in 4.2.2.2, resulting in a *method library*.

4.2.2.1 Analytical Capability

Based on Alter (1977) and others, introduced in 2.2.3.3, five classes of DSS are distinguished by analytical capability (AC) level, which can be built using different modelling methods. These classes include *descriptive*, *diagnostic*, *predictive* and *prescriptive* models. *Partially prescriptive* models exist between predictive and prescriptive models. The framework presented here focuses on predictive, partially prescriptive, and prescriptive models. Nevertheless, descriptive and diagnostic models play important roles in decision-making and should be used especially in unstructured decision situations.

4.2.2.1.1 Influences on Desired Analytical Capability

To determine the suitable AC, an influence analysis was conducted using the decision situation characteristics introduced in 4.2.1.3, followed by a pairwise comparison to determine the importance of each influence. The influences on the desired AC can follow several patterns, as portrayed in Figure 4-4[20]. To determine the desired AC, the

[20] Whereas positive and negative influences are self-explanatory, the other types are more complex. The type *prohibitive* is, for example, used for uncertainty (DC04), where low levels of uncertainty have very little influence on the choice of AC, but uncertainty beyond a specific point makes the high AC methods so inefficient and ineffective that lower AC is preferable. Similarly, the *necessary* relation requires a minimum level of influence before levelling out, and the *enforcing* relation requires high AC for low levels but has no effect for higher influence levels.

influencing characteristics are assessed on a six-point Likert scale, and the resulting influences contribute to a weighted sum.

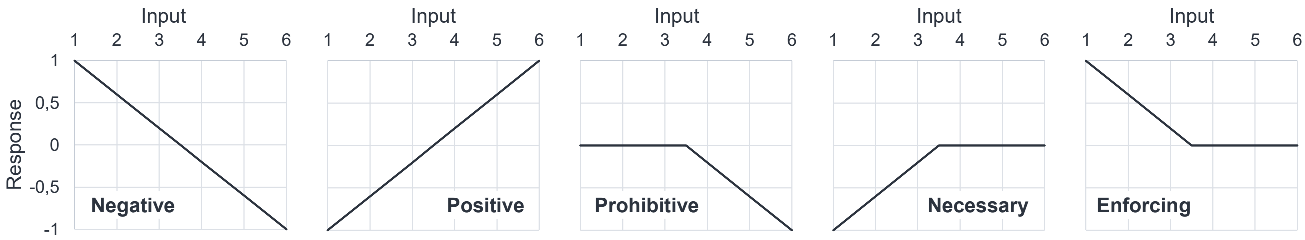

Figure 4-4: Types of Influences on AC Desirability

Table 4-7 displays and describes the considered influences on the desirable AC.

Table 4-7: Influences on Desired AC of a DSS for a PNC Task

Decision Situation Characteristic		Influence Description	Type
DC 01	System Linearity	The degree to which the system's behaviour is nonlinear increases the complexity of computations.	Positive
DC 02	Number of Decision Variables	The number of independent decision variables is positively associated with AC, as the combinatorial complexity is inaccessible to human decision makers.	Positive
DC 03	System Expertise	The DMC's expertise regarding the system's behaviour determines the necessary level of AC. Low levels enforce higher levels of AC, as the expertise to explore desirable options is missing.	Enforcing
DC 04	Uncertainty	High uncertainty regarding system behaviour and environmental development requires stochastic modelling and robust decision-making, which increases computational complexity, especially in prescriptive models, thus making them less attractive.	Prohibitive
DC 05	Decision Frequency	A higher frequency of similar decisions is positively associated with AC, as the increased use of these models offsets investments in more complex models.	Positive
DC 06	Decision Routine	Higher AC is more attractive in routine, well-structured decision situations	Positive
DC 07	Development Capabilities	Higher development capabilities make DSS with higher AC more attainable	Necessary
DC 08	Perspective Diversity	A high diversity of perspectives makes high levels of AC more challenging to achieve	Negative
DC 09	Achievable Accuracy	Higher achievable accuracy, due to the availability of data and model characteristics, makes higher AC more desirable, as the prescriptions can be trusted.	Positive
DC 10	Objective Quantifiability	The degree to which all of the objectives of the decision can be quantified increases the attractiveness of a higher AC.	Positive
DC 11	Data Acquisition Intensity	The required effort to acquire data for each alternative is negatively associated with AC, as only a limited number of alternatives can be tested if the effort is very high, and complete enumeration is not feasible.	Negative
DC 12	Time Horizon	Longer decision consequence horizons are associated with more complex systems, which cannot be captured with high AC.	Negative
DC 13	Decision Time	The time to make decisions can enforce a high level of AC, as the time for manual exploration of the solution space is not available.	Enforcing
DC 14	Computing Capabilities	Higher computing capabilities negate the computational complexity of higher AC and make it more attractive.	Necessary
DC 15	Desired Explainability	The explainability of decisions the DMC desires is negatively associated with AC, as prescriptive models still struggle to make reasoning for the chosen alternatives accessible.	Negative
DC 16	Model Expertise	Expertise regarding the structure and nature of relevant models in the DMC is positively associated with AC, as the higher complexity may be deployed more appropriately.	Positive

Figure 4-5 shows a pairwise comparison of the influences in the set $J^{(DS)}$.

	DC 01	DC 02	DC 03	DC 04	DC 05	DC 06	DC 07	DC 08	DC 09	DC 10	DC 11	DC 12	DC 13	DC 14	DC 15	DC 16	Sum	Weight
DC01 System Linearity		1	2	2	1	1	1	2	1	0	2	1	0	2	2	2	22	0.08
DC02 Number of Decision Variables	1		2	2	1	2	2	2	2	1	2	1	1	2	2	2	27	0.10
DC03 System Expertise	0	0		0	0	0	0	1	0	0	0	0	0	1	1	1	6	0.02
DC04 Uncertainty	0	0	2		0	0	1	2	2	0	0	0	0	2	2	2	15	0.06
DC05 Decision Frequency	1	1	2	2		1	2	2	2	1	2	1	1	2	2	2	26	0.10
DC06 Decision Routine	1	0	2	2	1		2	2	1	0	2	1	0	2	2	2	22	0.08
DC07 Development Capabilities	1	0	2	1	0	0		1	0	0	0	0	0	2	1	2	12	0.04
DC08 Perspective Diversity	0	0	1	0	0	0	1		0	0	0	0	0	2	1	2	9	0.03
DC09 Achievable Accuracy	1	0	2	0	0	1	2	2		0	2	0	0	2	1	2	17	0.06
DC10 Objective Quantifiability	2	1	2	2	1	2	2	2	2		2	1	1	2	2	2	28	0.10
DC11 Data Acquisition Intensity	0	0	2	2	0	0	2	2	0	0		0	0	2	1	2	15	0.06
DC12 Time Horizon	1	1	2	2	1	1	2	2	2	1	2		1	2	2	2	26	0.10
DC13 Decision Time	2	1	2	2	1	2	2	2	2	1	2	1		2	2	2	28	0.10
DC14 Computing Capabilities	0	0	1	0	0	0	0	0	0	0	0	0	0		0	1	4	0.01
DC15 Desired Explainability	0	0	1	0	0	0	1	1	1	0	1	0	0	2		2	11	0.04
DC16 Model Expertise	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0		4	0.01
																Total	**272**	**1**

Figure 4-5: Pairwise Comparison of Influences on Desired AC

To strengthen the representation of smaller influences, a base value of $v_{j,j}^{(IC)} = 2$ is used. The weight $w_{j_1}^{(ACDS)}$ on the AC of each influence j_1 is:

$$w_{j_1}^{(ACDS)} = \frac{\sum_{j_2 \in J^{(DS)}} v_{j_1,j_2}^{(IC)}}{\sum_{j_3 \in J^{(DS)}} \sum_{j_2 \in J^{(DS)}} v_{j_2,j_3}^{(IC)}} \forall j_1, j_2, j_3 \in J^{(DS)} \qquad \text{Equation 4-2}$$

Using these weights, the influence function $f_j^{(IT)}$ according to the type discussed above, and the influence value $v_{\pi,j}^{(IV)}$ the desirability of high AC in a decision process $W_\pi^{(AC)}$ can be estimated:

$$W_\pi^{(AC)} = \sum_{j \in J^{(DS)}} \left(w_j^{(ACDS)} f_j^{(IT)} \left(v_{\pi,j}^{(IV)} \right) \right) \qquad \text{Equation 4-3}$$

$W_\pi^{(AC)} > 0.15$ indicates prescriptive models, $0.15 > W_\pi^{(AC)} > -0.15$ a partially prescriptive model and $W_\pi^{(AC)} < -0.15$ predictive models. This assessment is only an indication and should be discussed and considered in the specific context of the planned DSS.

4.2.2.1.2 Decision Variable Sets

DSS and their underlying models exist in a context of other models that may interact with them. A model design cognizant of these relationships requires a systematic description of model relationships. The concept of decision variable sets introduced in 4.2.1.2.2 can be extended to models $m \in M_\pi$ used for a decision process π, with $\bigcup_{m \in M_\pi} X_m \subseteq X_\pi$. The set of decision variables X_m of a model m can be subdivided into a predictive set $X_m^{(PDC)}$ consisting of all variables that are not prescribed by the model and a set of prescribed variables $X_m^{(PSC)}$. Figure 4-6 shows the resulting five decision variable sets for each model when also distinguishing fixed, subject, and inconsequential variables[21]. For full predictive models, $X_m^{(SUB,PSC)} = \emptyset$, and for full prescriptive models, $X_m^{(SUB,PDC)} = \emptyset$[22]. The distinction of these sets becomes particularly important when considering the relationships between different models, which are discussed in 4.2.4.2.

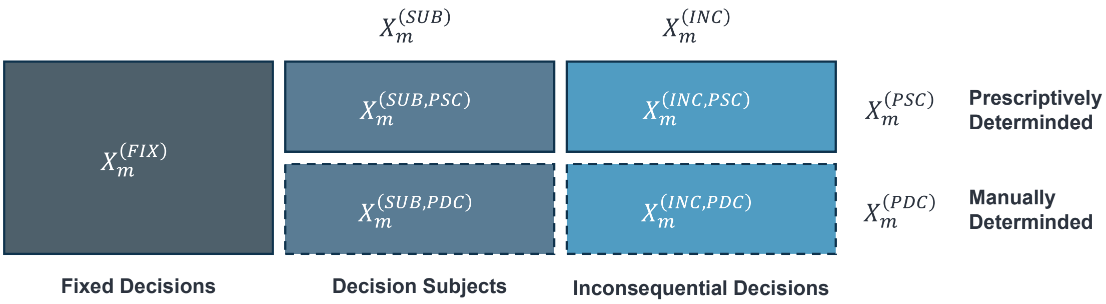

Figure 4-6: Sets of Decision Variables of a Generic Model

4.2.2.2 Method Selection & Library

The Method Library contains methods for (i) *scenario generation*, (ii) *configuration*, (iii) *prescription*, (iv) *prediction*, (v) *decision-making*, and (vi) *metamodeling*. These methods, as shown in Table 2-2, are collected from existing approaches that describe decision support in PNC. To effectively choose methods, their characteristics, their relation to the decision situation, and the relation between multiple methods must be considered. Thus, a literature and theory-based analysis of these aspects is performed. The resulting description of all considered methods is depicted in Figure 4-7.

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[21] The decision variable sets are determined only for the specific model instance used in a decision process. Since models can serve multiple decision-making processes, variable attribution to different sets may vary.

[22] A partially prescriptive model that aids capability and capacity decision-making may be used as an illustrative example. Assuming the decision-makers need to decide which production technologies and associated machine tools to allocate to each of their production sites. To this end, an optimisation model may be used as a partially prescriptive model. For this, the sites and their area may be considered fixed, i.e., $X_m^{(FIX)}$, as they cannot be changed in that decision. The decision on the allocated technology may be subject to strategic deliberations and competition between sites, so the decision-makers determine a set of alternatives they want to consider manually, i.e., $X_m^{(SUB,PDC)}$. Within these alternatives, the number of required machine tools for each technology must also be determined. This decision is primarily cost-driven and shall be determined by an optimisation model, i.e., $X_m^{(SUB,PSC)}$. To decide on machine tool allocation, decision-makers also need to determine which customers will be served from which location, and what transport route and mode to use. Both decisions only need to be plausible, as they may be revoked at a later point. The customer allocation shall be part of the optimisation model and thereby prescriptively determined ($X_m^{(INC,PSC)}$) whereas the transport route and mode shall be decided based on experience by a consulted logistics expert for each translation ($X_m^{(INC,PDC)}$).

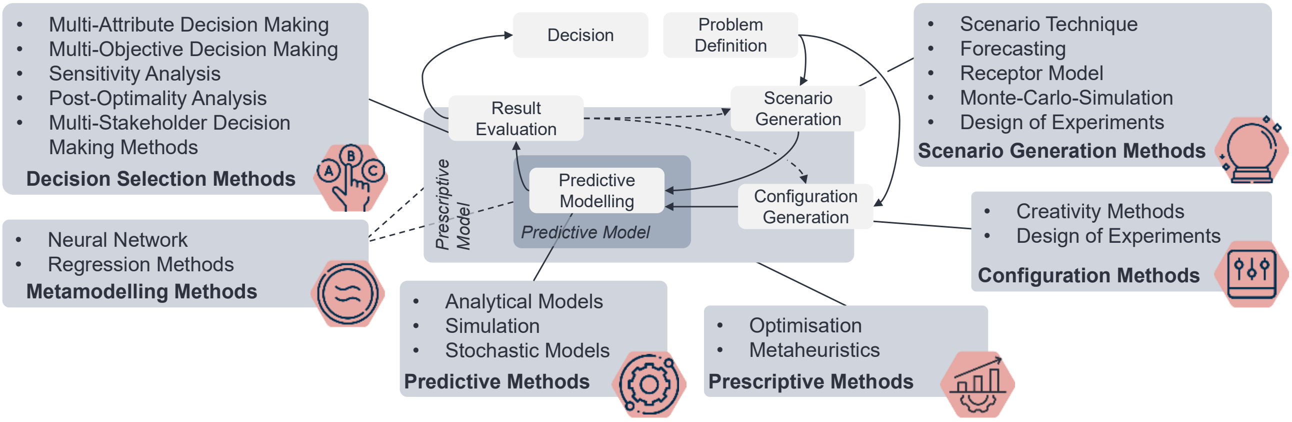

Figure 4-7: Overview of Method Library and Relation to the Decision-Making Process

The structure of the resulting method library is organised based on the previously introduced decision-making process. Figure 4-7 illustrates the relationship between the methods and the process. It also portrays predictive models, which only cover the predictive modelling step, and prescriptive models, which also contain parts of the scenario and configuration generation, as well as result evaluation. A detailed description of the mentioned methods is provided in Appendix A1. Furthermore, interactions with the decision situation and between methods are described in Appendix A2.8.

4.2.3 DSS Design Process

This subsection presents a structured process that aids in the design of DSSs for specific situations. This process, as portrayed in Figure 4-8, utilises different aspects of the previously introduced framework and library, aiming to simplify and streamline the design process, but first and foremost, create fitting DSSs. The process is organised in three phases, from general and abstract to specific and detailed. Depending on the project's size, each phase can be carried out with more or fewer stakeholders involved. The first phase, *decision type analysis*, examines the type of decision to be made, determines the desired AC, and defines which objectives need to be considered when making a decision. The second phase, *method composition,* translates that decision situation into a union of different specific methods that form the DSS. Finally, the third phase, *model detailing,* is concerned with the details of the specific decision support, including the granularity at which different system aspects are captured, the division between aspects within the considered system and outside of it, and the detailed formulation that represents the system's behaviour.

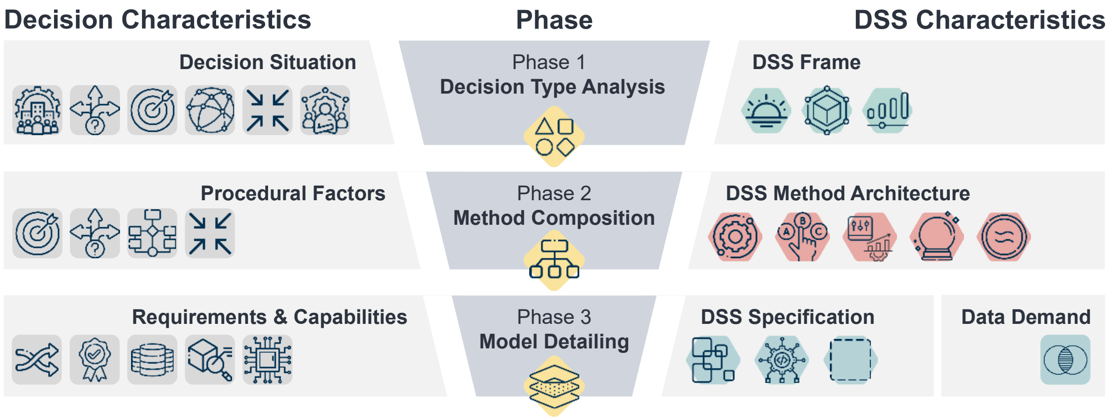

Figure 4-8: Systematic design process for PNC DSS

The process presented here is intended to apply to both decision types that are already established in an organisation in the form of a process and to decision types that currently lack a defined process. In the former case, many analytical steps can be accelerated, and existing information sources can be used. However, an existing process may limit the resulting DSS and should thus be challenged and adapted.

4.2.3.1 Phase 1: Decision Type Analysis

The first phase of the DSS design process aims to establish the outline of the later DSS. This outline, shown on the right-hand side of Figure 4-9, consists of the time horizon, the most important system elements to capture, and the desired analytical capability of the DSS.

Figure 4-9: Phase 1 - Decision Type Analysis

As the left-hand side of Figure 4-9 shows, the process leading to the DSS outline consists of three steps, each analysing relevant dimensions of the decision situation. The steps are organised in a way that allows for a sequential process, enabling all decisions regarding the DSS frame to be made. The following subsections provide a detailed description of each step.

4.2.3.1.1 Determination of the Time Horizon

As alluded to above, the time horizon of a DSS should be chosen as short as possible to minimise model complexity while capturing enough time to evaluate any allowed changes to the system comprehensively. Thus, first, the company's characteristics are analysed. The analysis culminates in a comprehensive assessment of company characteristics and a company-specific list of minimum times for changes to the system elements discussed earlier. Then, the lead decision variable is determined, i.e., the allowed change with the longest evaluation time. This evaluation time is the lower bound for the time horizon, whereas a practical time horizon is two times the length of the evaluation time. With the time horizon, the time usually available for the examined decision is also determined.

4.2.3.1.2 Selection of Major System Elements

The second step aims to select all system elements that must be captured in the DSS. The objectives considered in the decision-making process must be determined to prepare for this. At this point, determining precise measures is not yet necessary, as that also involves considering available information and computing capabilities. Instead, only the broad objectives shown in Table 4-3 are considered. These objectives should follow from the company's strategic objectives established in step one and be responsive to the influences set by the time horizon[23]. Subsequently, the domains to be considered need to be determined. The considered general domains are specified in 4.2.1.3.3. Depending on the organisation's structure, these domains may be subdivided based on markets, product families, production technologies or other aspects. Only domains with significant influence or interest in previously determined objectives should be considered to curb complexity. The system elements to be considered may be

[23] For example, decisions with short time horizons of 6 months can only influence a part of the production costs. The costs of long-term investments in large machine tools or production sites cannot be addressed within the specified time horizon.

determined based on objectives and domains. Only elements that influence the objectives and lie within the selected domains should be considered.

4.2.3.1.3 Deduction of Desired Analytical Capability

The final step of Phase 1 aims to determine the appropriate level of AC, which can be predictive, partially prescriptive, or prescriptive. First, the external influences affecting the decision are analysed. Relevant influences are determined by their effect on the selected objectives and system elements. At this point, a broad characterisation of influences and the degree to which they add uncertainty to the situation is sufficient. Secondly, the decision-making committee (DMC), i.e., the roles accountable and responsible for the decision, must be structured. They should cover all relevant domains and have authority on the leading decision variable. The composed DMC can then be described in terms of its competence with quantitative models and its system expertise.

With the previously acquired information, the desired AC is selected. As discussed in 4.2.2.1, this selection is influenced by numerous factors which may only be evaluated qualitatively. The strength and nature of each influence may only be estimated. Thus, for each influence listed in Table 4-7, a value $v_{\pi,j}^{(IV)}$ on a six-point Likert scale is selected, and a description of the influence is created. Using Equation 4-3, the weighed AC preference score $W_{\pi}^{(AC)}$ is calculated and assessed in comparison to the threshold value for AC levels. This score serves as a baseline for further discussion and ultimately AC level selection.

4.2.3.2 Phase 2: Method Composition

Whereas the first phase is focused on the broad strokes of the decision, phase two selects specific methods that constitute the DSS by building on a systematic understanding of the desired decision-making process. As shown in Figure 4-10, the procedural factors characterising the decision situation are considered, and the information obtained in Phase 1 is specified for selecting methods[24]. In this case, all procedural factors are analysed as described in 4.2.3.2.1 before the architecture of the DSS methods is designed following 4.2.3.2.2. The latter step takes into account dependencies of

[24] As indicated by the combined symbol, configuration and prescription methods are considered jointly, as they serve a similar function in determining the preferred configuration and are chosen by AC level.

methods vis-à-vis the procedural factors and dependencies between the selected methods as indicated by the arrows on the right side of Figure 4-10.

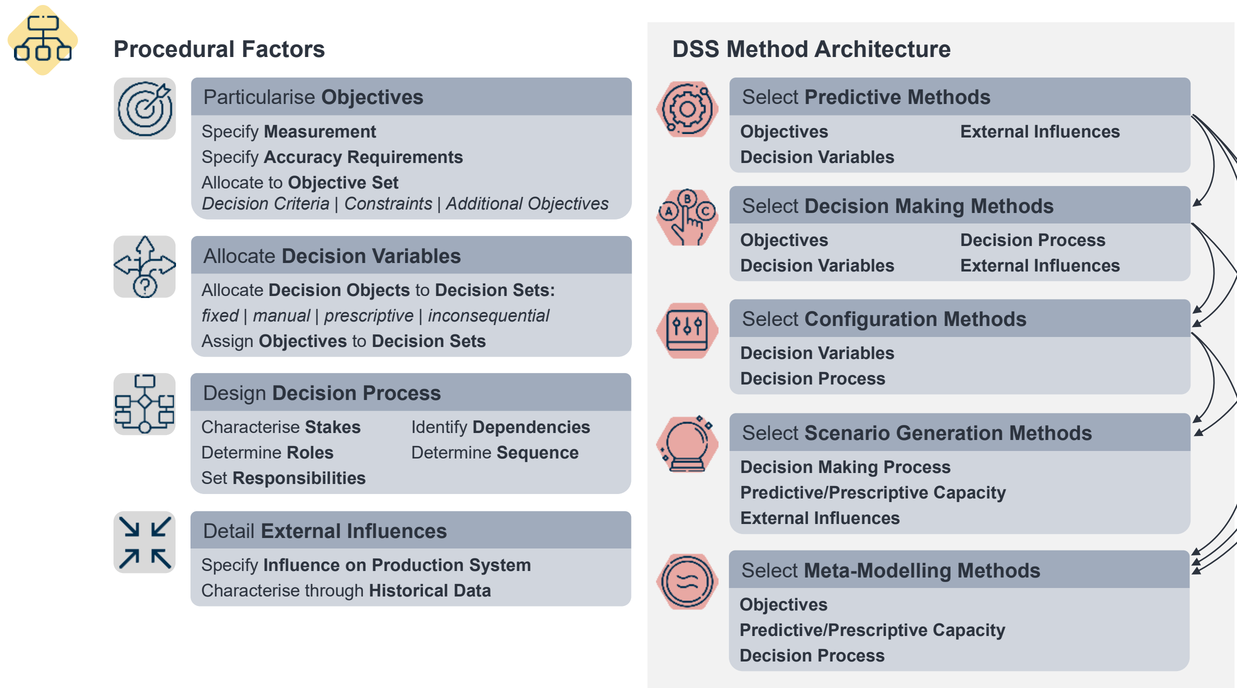

Figure 4-10: Phase 2 - Method Composition

4.2.3.2.1 Procedural Factors

The first step in Phase 2 is the *particularisation of objectives* determined in Phase 1, i.e., the specification of measurements for each objective and accuracy requirements towards the model. Furthermore, each objective's relevance and use in the decision-making is specified as either a decision criterion, a constraint, or an additional, optional objective by defining corresponding sets of objectives $G^{(DC)}$, $G^{(CON)}$, $G^{(OPT)}$.

Subsequently, the *external influences* identified in Phase 1 are *detailed* and characterised. The characterisation of influences involves their occurrence, i.e., regularity, frequency, detectability, and anticipated effect on the system. Information on different influences may be gathered from historical data and literature.

Next, *decision variables are allocated* to decision sets. As explained in 4.2.1.2.2, decision variables may be fixed, manually determined (predictive set), prescriptively determined (prescriptive set), or inconsequential. The DSS design team must then decide whether to choose different decision variables based on differentiated objectives. If so, objectives need to be assigned to the different decision sets. A typical example would be using monetary and IP-related objectives for technology-site allocation, while using only monetary objectives for product type allocation. In partially prescriptive models with non-quantitative objectives, a differentiated assignment of objectives is mandatory, as the qualitative objectives cannot be used for the prescriptive part of the model.

The *design of the decision process* builds upon Phase 1, where responsible and accountable roles are defined. Now, the stakes of these roles and additional ones, as they pertain to the decision-making process, need to be identified. Roles that need to contribute or be informed are identified and described. Finally, the decision process is modelled as a business process using BPMN. The modelling is oriented around the generalised decision-making process shown in Figure 4-3.

4.2.3.2.2 DSS Method Architecture

After the necessary procedural factors have been established, the method architecture of the DSS is designed. Based on the previously established dependencies of different methods, a sequential process of selecting (i) the predictive methods, (ii) the configuration methods, (iii) the decision selection methods, (iv) the scenario generation methods, and (v) the meta-modelling methods is used. In the following, the primary considerations for each are discussed.

Predictive methods make up the core of the DSS. For each decision set, at least one predictive method must be chosen[25]. In general, linear modelling or mixed-integer modelling is preferable when a more complex method is not otherwise required. While this general direction is relatively lax for predictive sets, it is crucial for the prescriptive sets. The granularity of decision variables largely determines the choice between linear and mixed integer linear models. Non-linear models may be necessary due to specific requirements imposed by objectives. High levels of uncertainty may enforce the use of stochastic or probabilistic models.

When both the predictive methods and are selected, the *configuration/prescription methods* can be chosen. Different creativity techniques can be used for the predictive set applied in a group decision-making process. Statistic methods may be used to structure experiments when many configurative choices are available. For the prescriptive

[25] As Figure 4-7 shows, a prescriptive model always contains a predictive model. Thus, a predictive method has to be chosen even for the prescriptive sets.

set, the choice of prescription method primarily depends on the chosen predictive method. Specialised methods[26] should be applied where possible to improve efficiency.

The *decision selection methods* can then be chosen. When qualitative objectives are relevant, multi-attribute decision-making methods are usually necessary. If the multiple objectives are part of the prescriptive set, multi-objective decision-making methods are required. Different variants of these methods can be chosen depending on the available decision time and the desired level of involvement from decision-makers. If decisions and aspects of the fixed set need to be challenged or contingency plans[27] are required, post-optimality techniques should be applied.

The selection of *scenario generating methods* needs to consider the nature of external influences, the modelling capacity, and the decision-making process overall. For cases with high uncertainty, a more elaborate scenario generation is necessary. For various stochastic influences, statistical techniques or Monte Carlo Simulation (MCS) can be employed. If decision-maker involvement is high and external influences are best described in long-term scenarios, variants of the scenario technique can be used. Shorter decision times and lower relative computation capacity restrict the extent to which scenarios can be considered.

Finally, short decision-making times and insufficient computational capacity can be overcome using *meta-modelling techniques*. They can be applied to represent both predictive and prescriptive models. When representing predictive models with many decision variables, linearization methods like multi-adaptive regression splines (MARS) are desirable to enable mixed-integer linear programming (MILP) methods. For short decision-making times and when the ability to generate meaningful synthetic data exists, neural networks (NNs) are particularly well-suited. The selection of meta-modelling techniques may necessitate reconsidering previous methods.

The presented procedure assumes that a DSS is designed without any other DSSs that may interact with it. When another DSS already exists, which determines some of the

[26] Here, specialised refers to methods that take advantage of limitations placed on the predictive model, such as enforcing linearity, as such methods generally offer benefits in terms of their computational efficiency to result optimality trade-off. Such methods can, however, only be chosen if corresponding predictive methods can represent the system's behaviour with adequate accuracy.

[27] Contingency plans, i.e., prescribed plans for a possible event, enhance the resilience of systems by increasing decision-making speed. They are particularly suitable in volatile environments and situations where the incurred performance drop scales directly with reaction time. (Benfer, & Verhaelen et al., 2021, p. 506)

parameters of the to-be-designed DSS or uses its outputs, these relationships must be considered in the composition of the method. The type of relationships and strategies to address them are discussed in 4.2.4.

4.2.3.3 Phase 3: Model Detailing

The third stage of the DSS design process focuses on the details of the methods, resulting in a complete conceptual model of the DSS. The procedure for this last phase is based on Benfer et al. (2019), a previous publication by the author, suggesting a systematic method for determining the abstraction level. This last phase also requires a more iterative procedure, as many aspects of the final model may not be apparent a priori. Figure 4-11 portrays this third phase, which is divided into two steps: requirements and restrictions, and DSS specification. An additional result of this phase is an overview of data demands created by the particular DSS.

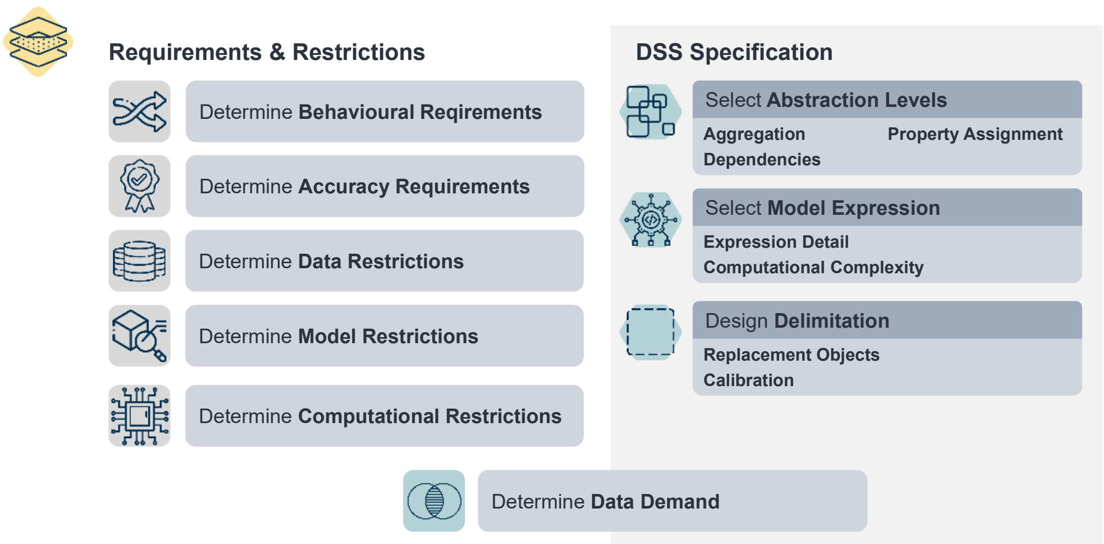

Figure 4-11: Phase 3 - Model Detailing

Whereas the previous two phases are intended for the one-time development of a DSS, this third phase may also be applied to instantiate a DSS for a unique problem instance. In 4.3.3, the creation of application models using the process discussed here is described. Furthermore, this phase focuses on specifying the predictive model at the centre of the DSS, whereas auxiliary methods are not considered further in this phase.

4.2.3.3.1 Requirements & Restrictions

Before the conceptual model of the DSS can be completed, the requirements and restrictions associated with it need to be considered. They are determined, cognizant of the already established decision-making process.

The first type of requirements to consider are *behavioural requirements*, characterised by the allowed changes. For each, the desired behaviour of the system representation should be described. For example, when a technology is allocated to a site, the site's production capabilities should change according to what the technology enables. *Accuracy requirements* specify the expected accuracy of the model representation. They are expressed in terms of the quantitative objectives of the decision and stated initially at the system level but may be further specified for different system elements and with respect to the elapsed time. *Data restrictions* are limitations to modelling imposed by missing data. They are dynamically captured as data sources are identified. These restrictions may be limited data granularity, limited data availability on specific system elements, or restricted data quality. *Model restrictions* are limitations on the achievable validity imposed by the methods used. These restrictions are primarily known from Phase 2. Furthermore, model restrictions may enforce a minimum level of granularity. Lastly, *computational restrictions* limit the possible computational complexity of the addressable problem. Typically, computation restrictions are stated as limitations of the acceptable computing time for solving a problem, either predictively or prescriptively.

4.2.3.3.2 DSS Specification

To tailor the model to its application, three characteristics need to be addressed: (i) the *abstraction level* of system elements, (ii) the *expression of system behaviour* in the model, and (iii) the *delimitation* of the examined system concerning its environment. These transformations are illustrated in Figure 4-12.

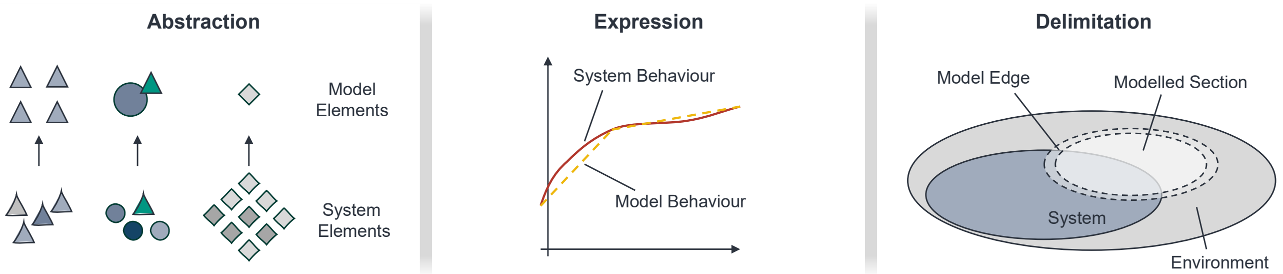

Figure 4-12: DSS Specification through Abstraction, Expression, and Delimitation

The *abstraction level* describes the level at which different elements in the predictive model are considered and distinguished[28]. As production systems are constituted of multiple fractal objects, i.e. objects that contain elements with similar properties, the same model logic can be applied at different levels of abstraction (Martin, & Peukert et al., 2023, p. 686). The highest level of abstraction that fulfils the behavioural and accuracy requirements should be chosen to make the model as simple as possible. The PNC element library offered in Appendix A2.5 contains suitable abstraction levels for the different elements in PNC. Depending on the selected model, choosing an abstraction level for one PNC element type can enforce a minimum granularity for another type. This issue and how it can be resolved by modelling dependencies between element types is described by Benfer et al. (2019) and is further discussed in 4.3.3.2. Higher abstraction levels can significantly reduce computing demands, as the number of model elements is reduced.

Model expression describes variations in the particular functional description of system behaviour. For example, transportation costs can be calculated as a fixed rate for a given route and item, or as a more complex function of the transportation demand on a given route[29]. The chosen model expression can significantly impact the model complexity, accuracy, and data demands and depends on the particular circumstances of the modelled system.

Delimitation describes the determination and specification of the boundary of the predictive model, which only reproduces a part of the system. Whereas the previous two aspects described the static and dynamic representation precision, i.e. inner limits of the model, delimitation is concerned with the outer limits of the considered system. The system's boundaries are typically limited to the system the DMC has authority over, which may be specified by the functional perspective of the members, their assigned product groups, markets, etc. Sometimes, the focal system may be narrowed further to address a particular problem. Correspondingly, the model's outer limits are determined

[28] As illustrated in Figure 4-12, this can involve representing an element with generic representations or aggregating them into one representative element with characteristics that reflect either their sum or average, depending on the characteristic and its use in a model. For example, production equipment at a site can be differentiated by aggregating into machines with the same production technology, or multiple machines that are part of a flow production can be considered as a single piece of equipment.

[29] These representations should always conform to the chosen predictive model type, e.g., only linear representations are possible in linear models. If a conforming representation is not suitable, a return to phase two of the design process may be necessary.

based on a selection of several dimensions: (i) functional domains, (ii) products, (iii) markets, (iv) components, and (v) production processes[30]. For each dimension, a set of instances inside the model is determined. However, elements within the model can interact dynamically with elements outside the model. For example, production stations may be used for products inside and outside the model scope, so omitting outside components would distort production costs. Introducing replacement elements designed according to the model behaviour and the delimitation dimension addresses this problem while limiting model complexity. Replacement element design is discussed in 4.3.3.4.

4.2.3.3.3 Data Demands

Generally, data demands are inferred from properties used in the DSS. Thus, a mapping is created that directly relates elements and properties in the model to the necessary data obtained from the database (DB) discussed in 4.3.1. The data types used in the model can be index sets of elements, categorical allocations and descriptions, or numerical properties. The first describes the existence of an element, while the latter describes its properties. Each unique type of element or property can be characterised as a data demand d.

For each $d \in D_m$, requirements specifying data accuracy and timeliness as described in 2.3.1 can be determined. The specification of accuracy demands depends on the type of demand. For set demands, accuracy may be defined in terms of the set's distinction granularity and its classification's specificity and sensitivity. For categorical demands, the accuracy may also be described by the specificity and sensitivity of the category allocation. Whereas the accuracy for the first two may only be characterised in terms of the average across a set of demands, numerical demands can also be expressed with regard to individual demand items. The accuracy can be described in terms of permissible average deviation and permissible deviation, either relative to the value or in absolute terms. The timeliness requirements can be expressed as the highest permissible information age for all three demand types. In addition, requirements for the other data quality aspects specified in 2.3.1, including consistency, completeness, believability, and interpretability, can be established.

[30] The characteristics by which the system is delimited correspond to the particular decision considered. These characteristics tend to align with the focal organisation’s structure as described in 2.1.1, but may also be influenced by decision process characteristics and focal company characteristics.

The requirements towards data demands should be specified based on expert judgement and the accuracy requirements towards the DSS, as a detailed analysis of every demand is likely not worthwhile. The previously determined abstraction level is used to meet the granularity requirements of the set demands. Specificity and sensitivity demands may be determined by considering the consequences of false positives or false negatives. For numerical accuracy, consequences can be estimated or tested using sensitivity analysis based on the accuracy requirements towards the DSS.

4.2.4 Multi-DSS Design

In many circumstances, PNC tasks overlap and interlock with each other. In the previous sections, the DSSs are designed assuming only one decision process and subsequently one DSS. However, different decision processes interact with one another, as they may require information from each other or affect the same elements within a GPN. While such dependencies or conflicts can be resolved in manual processes through sequencing or communication, conflicts may invalidate the decisions derived from automated processes. Thus, decision process design and DSS design should address such relationships to avoid undesired consequences.

This section develops a framework that describes the relationships between multiple decision processes in 4.2.4.1 and between models in 4.2.4.2. To address the different relationships, 4.2.4.3 develops several strategies. The resulting approach for multi-DSS design can be integrated into Phase 2 of the DSS design process, as described in 4.2.3, specifically in the consideration of procedural factors outlined in 4.2.3.2.1.

4.2.4.1 Relationships Between Multiple Decision Processes

The decision variable framework for configuration decisions, introduced in 4.2.1.3.4, can be used to describe the relationship between two decision processes $\pi_1, \pi_2 \in \Pi$, where Π denotes the set of all decision processes. For both processes a set of fixed decision variables $X_{\pi_i}^{(FIX)}$, a set of subject variables $X_{\pi_i}^{(SUB)}$, and a set of inconsequential variables $X_{\pi_i}^{(INC)}$ may be defined. Using these decision variables, three basic relationships can be defined. If $X_{\pi_1}^{(SUB)} \cap X_{\pi_2}^{(FIX)} \neq \emptyset$ and π_2 may be called *dependent* on π_1, as the latter at least partially defines the circumstances of the former. If $X_{\pi_1}^{(SUB)} \cap X_{\pi_2}^{(SUB)} \neq \emptyset$, both processes shall be called *conflicting*, as both are responsible for the same alterations. Lastly, π_2 is a *realisation* of π_1 if $X_{\pi_1}^{(INC)} \cap X_{\pi_2}^{(SUB)} \neq \emptyset$[31]. A special case occurs for $(X_{\pi_1}^{(SUB)} \cap X_{\pi_2}^{(FIX)} \neq \emptyset) \wedge (X_{\pi_2}^{(SUB)} \cap X_{\pi_1}^{(FIX)} \neq \emptyset)$, here the processes are *interlocked* as they depend on each other.

4.2.4.2 Relationships Between Multiple Models

Next, the models used to support the decisions are considered. The relationships between different models can be described with the same vocabulary as those between decision processes. However, as explained in 4.2.2.1.2, a distinction must be made between the predictive and prescriptive sets[32]. Considering this distinction, eleven primary and three secondary relationships exist between models. In the following, a nomenclature for these relationships is developed, with specific arrow types used to describe each relationship. An example of each relationship is given in Appendix A2.9.

The primary relationships displayed in Figure 4-13, are structured according to the process relationships above into dependencies, conflicts, and realisations. Relationships are defined based on overlapping sets of decision variables, except for the *independent from* and *non-conflicting* relationships, which denote the absence of overlap[33]. In addition, there are two dependence relationships, three conflict relationships, and four realisation relationships.

In addition to the presented primary relationships, three secondary relationships[34] shall be introduced. A model m_1 is *hierarchically superior* to m_2 if:

$$m_1 \Rrightarrow m_2 \coloneqq (m_1 \Rightarrow m_2) \wedge (m_1 \nLeftarrow m_2) \qquad \textit{Equation 4-4}$$

Furthermore m_1 and m_2 shall be called *interlocked* if:

$$m_1 \rightleftharpoons m_2 \coloneqq (m_1 \Rightarrow m_2) \wedge (m_1 \Leftarrow m_2) \qquad \textit{Equation 4-5}$$

---

31 A systematic assessment of possible relations between the decision variable sets would also yield relations between two fixed sets, a fixed and an inconsequential set, and two inconsequential sets. However, these relations are found to have no meaningful impact on the resulting relation between two processes. Thus, they are excluded from this analysis.

32 This distinction is necessary due to the closed nature of prescriptive models, which makes unifying competing objectives between the model and another way of finding decisions challenging.

33 These will henceforth be referred to as *negative* relationships, whereas overlapping relationships are referred to as *positive*.

34 In theory, combining primary relationships can identify many other secondary relationships. However, as far as they have been analysed for this work, they show no specific emergent behaviour that is not adequately described by the respective primary relationships.

Even though interlocking is a type of dependence relationship, it behaves very similarly to the conflict relationships, as will be highlighted in the next section. Lastly, m_1 is *semi-locked* by m_2 if:

$$m_1 \rightharpoonup m_2 \coloneqq (m_1 \Rightarrow m_2) \land (m_1 \longleftarrow m_2) \qquad \textit{Equation 4-6}$$

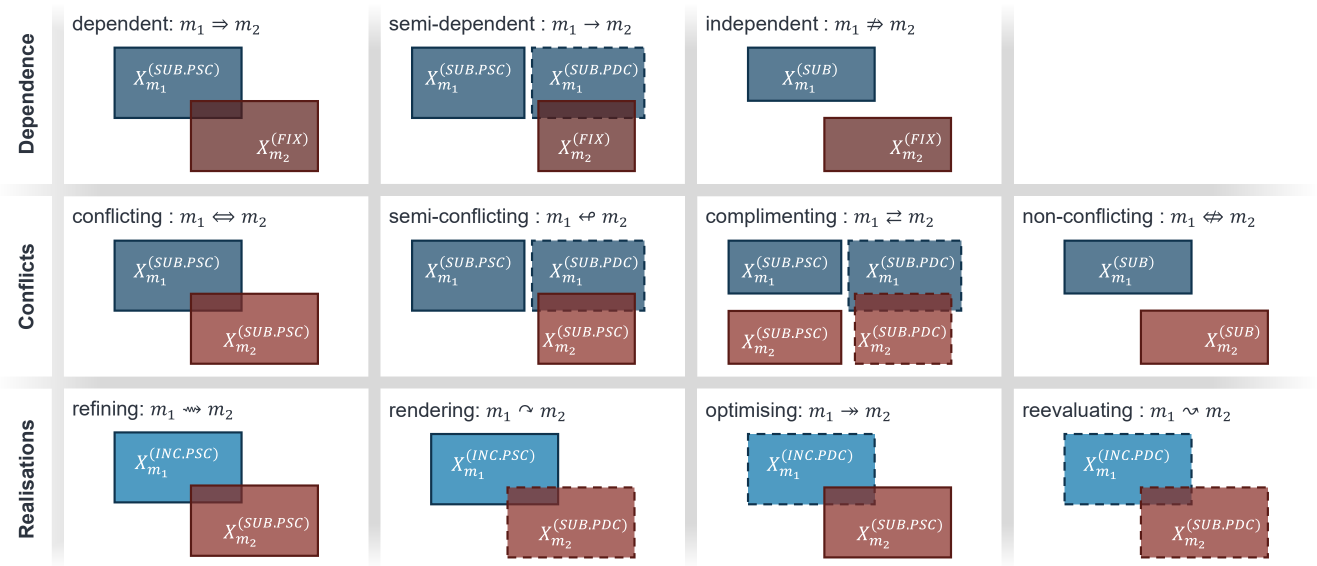

Figure 4-13: Types of Primary Model Relationships Based on Decision Variable Sets

4.2.4.3 Strategies to Address Model Relationships

The model relationships lead to consequences for multi-model systems. Some consequences can be considered, whereas others require specific strategies to avoid defective overall systems. Strategies resulting from a structured analysis, focusing on decision procedures and model characteristics, are possible for each case. An overview of the strategies is presented in Table 4-8 while a more detailed depiction and discussion may be found in Appendix A2.10. The following examines the challenges associated with dependence, locks, conflicts, and realisations, as well as the broad concept behind the strategies to address them. Unilaterally dependent and semi-dependent models create a ‘natural’ sequence as the dependent models require parameters from the other model. Thus, strategies seek to sequence them accordingly, either as an organisational measure or an automatism.

Unilaterally dependent and semi-dependent models create a ‘natural’ sequence as the dependent models require parameters from the other model. Thus, strategies seek to sequence them accordingly, either as an organisational measure or an automatism.

Table 4-8: Overview of Strategies to Address Model Relationships

Category	Addressed Relationship	Strategy	Strategy Type
Dependence	dependent, semi-dependent	sequence	organisational
		connect	procedural
Locks	interlocked	automatically iterate	
	interlocked and semi-locked	manually iterate	
		combine	model combination
		subsume	
		predictively explore	space combination
		prescriptively explore	
Conflicts	conflicting	combine	model combination
		subsume	
		clarify responsibility	organisational
		reduce capability	model change
		dynamically select trade-off	space combination
		predictively explore	
		prescriptively explore	
	complimenting	coordinate	organisational
		integrate	model combination
Realisations	refining, rendering	subsume	
	optimising	integrate	
	reevaluating	expand	
	all realisations	sequence decreasingly	organisational
	optimising, reevaluating	sequence increasingly	
	all realisations	trigger	procedural
		calibrate	

Locks do not allow sequencing, as both models depend on each other. One approach for this is iterative use, automatically or manually. Iteration strategies may include convergence-inducing measures and break criteria. Iteration cannot guarantee finding any dominant solutions. Another approach is to combine the models into one or subsume a model with a lower AC in the higher AC model. The possibility for this depends on organisational conditions and the specifics of the models. Finally, the locked feasible[35] decision space $\Phi_{m_1,m_2}^{(LOCK)}$ can be searched for an optimal solution. It is defined as

$$\Phi_{m_1,m_2}^{(LOCK)} = \Phi_{m_1}\left(X_{m_1}^{(SUB)} \cap X_{m_2}^{(FIX)}\right) \cup \Phi_{m_2}\left(X_{m_2}^{(SUB)} \cap X_{m_1}^{(FIX)}\right) \qquad \textit{Equation 4-7}$$

where $\Phi_{m_1}\left(X_{m_i}^{(SUB)} \cap X_{m_2}^{(FIX)}\right)$ denotes the decision space on the intersection of $X_{m_1}^{(SUB)}$ and $X_{m_2}^{(FIX)}$ that is feasible for m_1. Predictive exploration uses DoE approaches or full enumeration to find suitable solutions[36]. Prescriptive exploration uses meta-heuristics to search optimal or Pareto dominant solutions on $\Phi_{m_1,m_2}^{(LOCK)}$.

[35] The designation assumes that each model is solvable for any permissible set of parameters. If this assumption does not hold, the actual feasible space for the combination may be significantly smaller. Usually, the extent of the actual feasible space can only be determined ex post.
[36] Technically, a complete enumeration and two exact prescriptive models would resemble a dynamic programming problem.

Conflicts are similar to locks, but due to the direct overlap in decision-making competence, the difficulty they induce is even higher. In the case of conflicts between two decision-making processes, the organisation must clarify the responsibilities, even outside the consideration of DSS. For models, conflicts can be evaded by clarifying responsibilities such that $X^{(SUB)}_{m_1^{(NEW)}} \cap X^{(SUB)}_{m_2^{(NEW)}} = \emptyset$[37] and

$$X^{(FIX)}_{m_1^{(NEW)}} \cup X^{(FIX)}_{m_2^{(NEW)}} = X^{(FIX)}_{m_1} \cup X^{(FIX)}_{m_2} \cup \left(X^{(SUB)}_{m_1} \cap X^{(SUB)}_{m_2}\right) \qquad \textit{Equation 4-8}$$

When:

$$\left(X^{(FIX)}_{m_1^{(NEW)}} \backslash X^{(FIX)}_{m_1} \neq \emptyset\right) \wedge \left(X^{(FIX)}_{m_2^{(NEW)}} \backslash X^{(FIX)}_{m_2} \neq \emptyset\right) \qquad \textit{Equation 4-9}$$

a lock is created. Otherwise, a dependence occurs. If responsibilities cannot be clarified, the AC can be reduced for the intersecting decision variable set to create a complementary situation. Alternatively, models can be combined or subsumed. An iterative procedure available for locks is impossible for conflicts, as the conflicting models overwrite their respective decisions and thus do not converge[38]. Instead, the models can be modified to include a distance-from-start solution-based soft constraint, which can be modulated to allow a dynamic exploration of the range between the preferred solutions $\boldsymbol{x}_{m_1}, \boldsymbol{x}_{m_2}$ of both models. A more extensive discussion of this and the other strategies is provided in Appendix A2.10. Finally, conflicts can also be solved with a predictive or prescriptive exploration of the shared feasible decision space $\Phi^{(CONF)}_{m_1,m_2}$. However, in contrast to locks, here it is defined as the intersection between the constraints of both models.

$$\Phi^{(CONF)}_{m_1,m_2} = \Phi_{m_1}\left(\Phi_{m_2}\left(X^{(SUB)}_{m_1} \cap X^{(SUB)}_{m_2}\right)\right) \qquad \textit{Equation 4-10}$$

This space can then be explored using similar strategies to those for locks.

Complimenting models are a form of conflict that does not require model changes. As the conflicting decision variable space is manually determined, they do not overrule

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[37] Here, the superscript NEW denotes the revised models with adapted decision variable sets.
[38] Technically, a convergence is possible if non-exact, start-point-dependent prescriptive methods are used. Although convergence cannot be guaranteed even then, it is dependent on the existence of local optima. These local optima may also not even represent 'good' overall solutions.

each other. Their use should, however, be coordinated to use results from both models for a decision. Also, the models can be integrated directly if that is desirable.

Realisations do not require any strategy but present an opportunity for improved accuracy and reactivity. The relevant strategies are discussed in Appendix A2.10.

Generally, this section assumes a constellation of only two models in relation to each other. A constellation of more than two models may generally be structured into combinations of multiple two-model relationships, which may be addressed individually. The only exception are looped dependencies of $N^{(MOD)}$ models with

$$\forall i_1 \in N^{(MOD)} \exists i_2 \in N^{(MOD)}: X_{m_{i_2}}^{(SUB)} \cap X_{m_{i_1}}^{(FIX)} \neq \emptyset \qquad \text{Equation 4-11}$$

This multi-model relation shall be coined a *looped-lock*. The strategies proposed for locks can also be applied, though some adaptations may be necessary.

4.3 Digital Twin Architecture

To realise synergies between multiple DSS in PNC tasks, a common architecture for the DT of the GPN is necessary. This chapter addresses this requirement and PRQ2:

How can such DSSs be structured in an expandable form so that many different problems can be addressed?

At the core of the presented architecture lies a common data model (DM) and database (DB), which is developed in 4.3.1. The functionality provided to different DSS is outlined in 4.3.1.6. Finally, Section 4.3.3 discusses the generation and synchronisation of such DSS. An overview of this structure is provided in Figure 4-14.

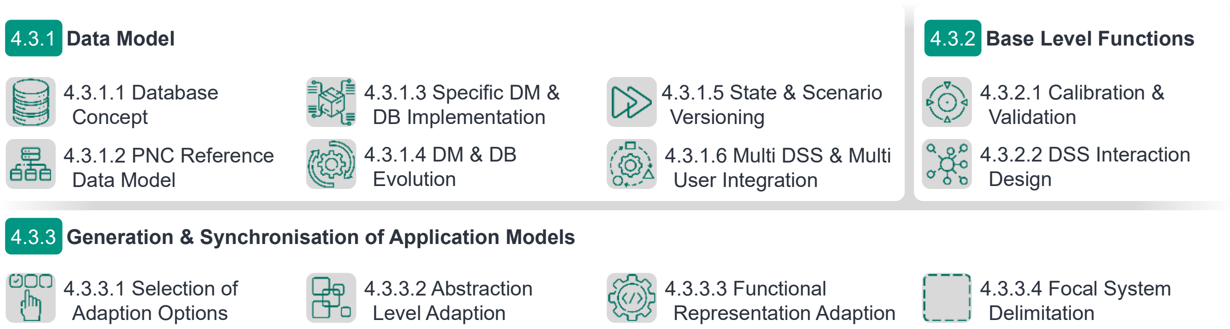

Figure 4-14: Overview of Section 4.3 – Digital Twin Architecture

4.3.1 Data Model

The DM serves as the foundation of all planning tasks within the DT. As such, it needs to include all necessary information for each DSS. Therefore, it must include all decision variables and necessary parameters. It should furthermore form a structure that reflects the relationships between the elements of the system and its environment. Finally, it needs to be compatible with multiple planning processes and store data on the current system state and planning data. The methodology to develop a suitable DM and the exemplary model presented are based on theses A_Orhan (2022) and A_Weidmann (2021), which were supervised by the author.

4.3.1.1 Database Concept

To accommodate several different DSSs focused on different PNC tasks, a DB must be very extensive, storing properties for each element. As data demands are often only uncovered during DSS design, an upfront definition of all properties would be very difficult, especially considering the decidedly iterative approach proposed for implementing the framework discussed in this work. However, a fully reactive DB design that only adds elements and properties when they are acutely needed would likely result in a convoluted, hard to manage and maintain data structure.

Thus, this work proposes a hybrid, modular approach, as shown in Figure 4-15. This approach consists of a reference DM developed using an analysis of relevant PNC tasks. This reference DM contains aspects used across PNC tasks, as well as aspects that are particularly important for specific tasks and considered domains.

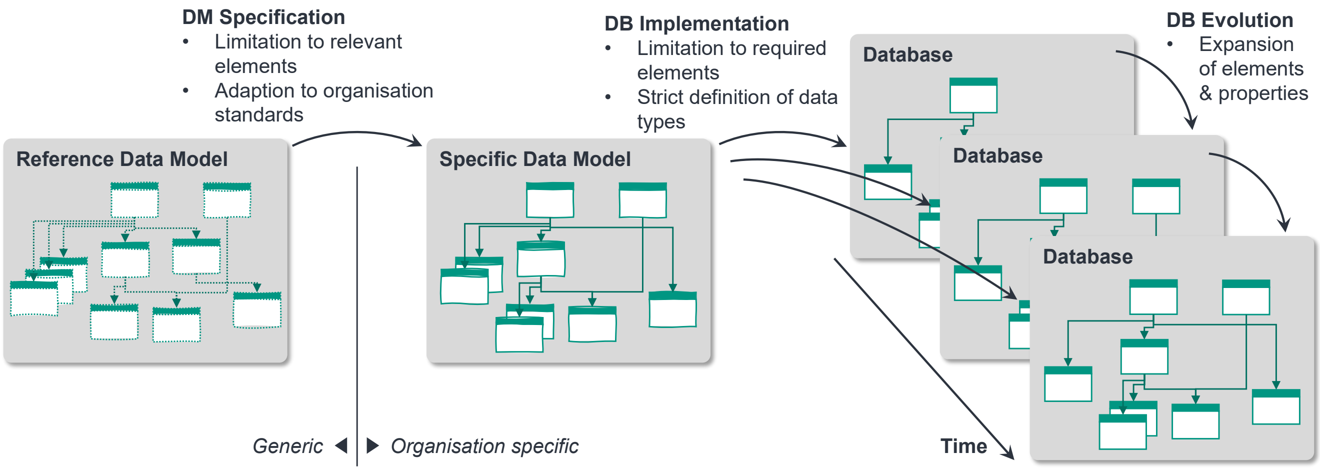

Figure 4-15: Relationship between PNC Reference Data Model, Organisation Specific Data Model, and Database

Organisations may specify their own DM from the reference DM, adapting it to existing definitions and important aspects of their specific production system. This DM is then implemented in either a relational or an object-oriented DB. In the DB, elements and properties that are part of the model core or immediately used by a DSS should be implemented. Additional elements and properties may be added to the DM when new DSS, additional DSS features, or new calibration functionalities are added.

This concept recognises that changes to the structure and hierarchy of DBs are disruptive, but additions of properties are possible without perturbing existing processes. Furthermore, the concept allows organisations to individualise their DM to suit their existing data landscape better.

4.3.1.2 PNC Reference Data Model

The Reference DM describes the relevant classes and their relationship in a UML model. It is designed based on an analysis of existing DMs in the literature, combined with examining relevant tasks that a model should support. The classes in the model originate from a literature-based analysis of typical PNC tasks and their data demands, as well as the PNC Element Library introduced in 4.2.1.3.4. These classes are organised in an object-oriented fashion, representing relevant characteristics and relations. To make the DM more accessible, it is organised in modules, such that relations are predominantly organised within the modules. Figure 4-16 shows an overview of the reference DM.

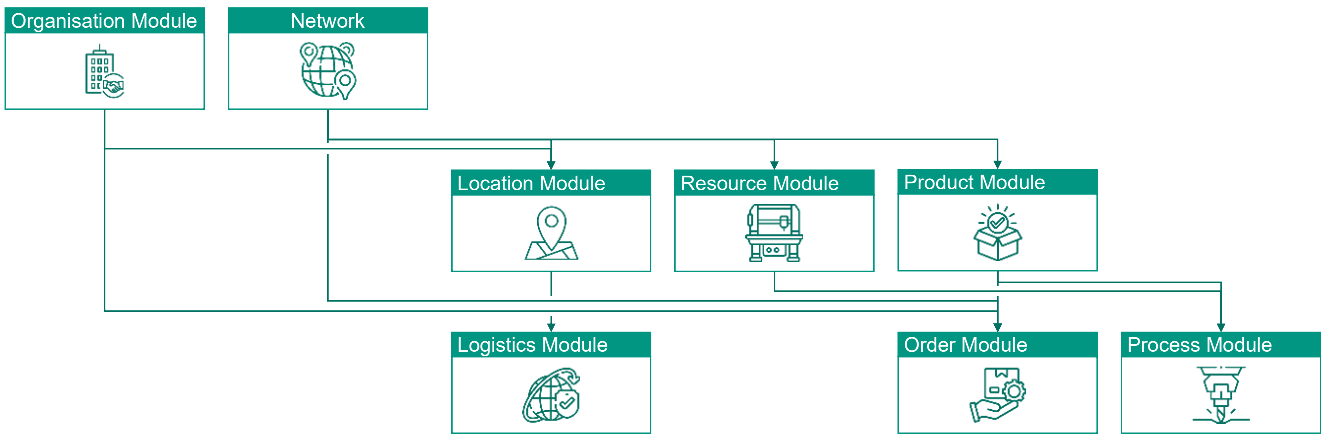

Figure 4-16: Overview of the PNC Reference Data Model

The DM is organised in eight distinct modules, each containing several classes. These modules are dedicated to the (i) focal *network*, (ii) *organisations*, (iii) *locations*, (iv) *resources*, (v) *products*, (vi) *logistics*, (vii) *orders*, and (viii) *processes*[39]. Both the design process and the detailed reference DM are portrayed in Appendix A3.1.

4.3.1.3 Specific Data Model & Database Implementation

When translating the Reference DM to an organisation-specific model, the main concerns are adherence to established definitions and specifics of the organisation's production system. The organisation-specific model should be designed to accommodate multiple considered DSS, as changes to the model may require structural changes to the derived DB, which may enforce adaptations to existing access scripts. The DB can be instantiated in different systems depending on the requirements and available resources of the deploying organisation. In most cases, the DM has to be amended to suit the chosen DB. Relational DBs require a data structure translation to include many-to-many relationships.

For the implementation of the DB, this work refers to the procedure proposed by Connolly and Begg (2015, pp. 506–507), with some adaptations to suit the specific use case and previous steps. Implementing the organisation-specific DM does not need to be exhaustive, as non-structural changes to the DB are usually non-invasive vis-à-vis existing access scripts. For the implementation, a set of element types $\hat{\mathrm{E}}^{(DES)}$ required by desired DSSs as specified in 4.2.3.3.3 is determined. This set is combined with all element types $\hat{e} \in \hat{\mathrm{E}}^{(REL)}$ necessary to reflect the relations within $\hat{\mathrm{E}}^{(DES)}$ to the implementation set $\hat{\mathrm{E}}^{(IMP)}$. Additionally, properties required by the DSS are implemented on $\hat{\mathrm{E}}^{(DES)}$.

4.3.1.4 Data Model & Database Evolution

The development of the DT may require updating of the DB and DM. While DB evolution is necessary for the described concept, DM evolution should be avoided. To record the evolution, DB and DM are both versioned. As will be discussed in 4.3.1.5 and 4.3.1.6, all information in the DB is assigned to a specific scenario version. As these scenario versions are only specified once, assigning each scenario version to the current DB version is sufficient to fully specify the DB version of all information in the DB. DB evolution may include the addition of element types or the addition of properties, neither of

[39] This module structure mainly depicts which elements are part of the DM and how they relate to each other. The modules thereby represent groups of elements which are closely linked and thematically connected. All elements of the PNC Element Library are contained.

which interrupts existing functionality. When such additions are made, those functions should be tested. To avoid issues, compatible DB versions may be stored for every functionality interacting with the DB.

4.3.1.5 State & Scenario Versioning

In contrast to most conventional DBs in production, the data for PNC includes master and status data, as well as operational plans. Transaction data is largely irrelevant for PNC[40], although it may be used to verify and update master and status data, or trigger event-based planning processes. The DB needs to be able to reflect changes in any of these types of data. The information in the DB needs to reflect the temporal development of the GPN. This information is not mandatory for planning, but it may be used in use cases beyond simple problem-solving and also enables calibration, which is explored in more detail in 4.3.2.1. Thus, past system states need to be captured in the DM. Only discretised past states should be stored to limit the necessary amount of data. While there are different possible alternatives for state discretisation, a fixed-timestep interval with intervals the size of the shortest supported planning interval is practical. Based on the characterisation of configurative changes discussed in 4.2.1.3.4, this should result in intervals ranging from weeks to half a year. Depending on the limits of the DB, states that lie further in the past may be thinned out dynamically.

Planning and status data are necessarily organised according to time intervals. However, organisations plan different system elements at various time horizons and intervals. Additionally, planning data is uncertain and represents only a partial description of the production network. Thus, the DB needs to contain data for multiple future states $y_{t,\omega}^{(PLAN)}$ that are characterised by the period t and the planning scenario[41] ω they belong to. This concept is depicted in Figure 4-17, which also shows past states and how multiple planning scenarios relate.

Planning scenarios ω are assigned to scenario spaces σ, which are sets of scenarios that originate at the same starting point $y_{\sigma}^{(START)}$ and are defined by the same owner $\mu_{\sigma}^{(OWN)}$ for the same model m_{σ}. Scenario spaces may contain three types of scenarios,

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[40] Most PNC tasks occur on time scales beyond the relevance of transaction data.

[41] Here, the term scenario is used even if the plan describes a configuration, as any DSS using the data will interpret it as an environment scenario.

one nominal scenario $\omega_\sigma^{(NOM)} \in \Omega_\sigma^{(ALT)}$, which is used for deterministic planning and acts as a baseline, alternative scenarios $\Omega_\sigma^{(ALT)}$, which describe expected alternatives as well as other scenarios $\Omega_\sigma^{(OTH)}$. Nominal scenarios and alternative scenarios are assigned an assumed probability of occurrence $\kappa_\omega^{(SC)}$ such that $\sum_{\omega \in \Omega_\sigma^{(ALT)}} \kappa_\omega^{(SC)} = 1$. These probabilities can be used as weights when other DSS create robust plans for a given scenario space. To represent continuous probability density functions (pdf), the parameters of the pdf may be stored in the states. Thereby robust planning may also use non-discretised pdf's when applicable.

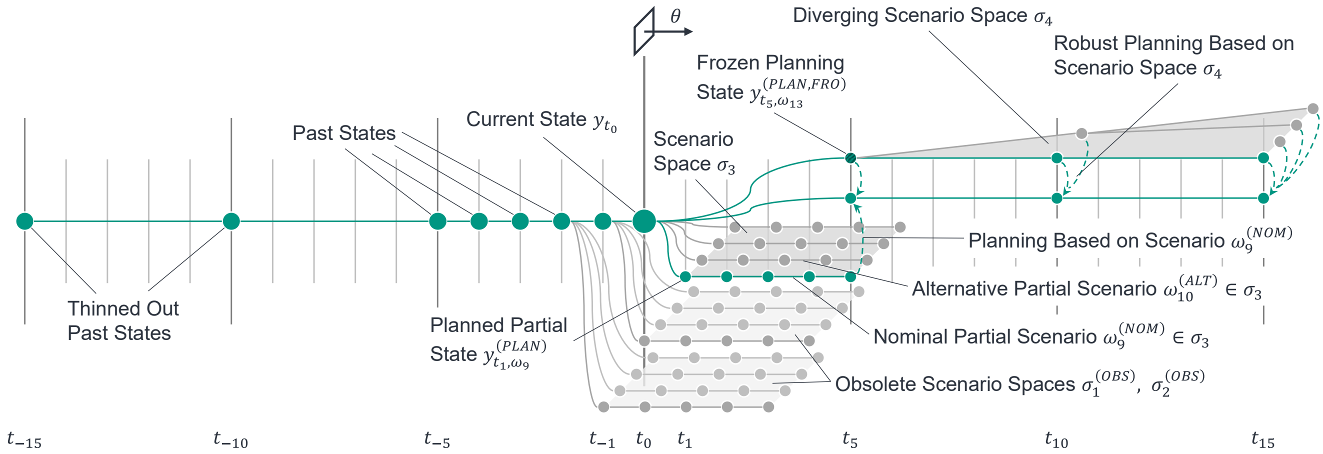

Figure 4-17: Versioning in the Database

The scenario spaces can also be used to support the necessary access rights management for sensitive plans in the DB. When the current timestep t is past the starting point of a scenario space, it may be marked as 'obsolete', as new data from the actual system may be available. Obsolete scenario spaces should not be deleted immediately, as insights may remain valid for some time.

For each scenario ω, additional characteristics are specified. The planning time period $t_\omega^{(PLAN)}$, the parent scenario $\omega_\omega^{(PAR)}$[42], the time of divergence $t_\omega^{(DIV)} | t^{(DIV)}_{\omega_\omega^{(PAR)}} < t_\omega^{(DIV)}$ and the set of scenarios $\Omega_\omega^{(REF)} \coloneqq \{\omega_i\}$ and the set of scenario spaces $\Sigma_\omega^{(REF)} \coloneqq \{\sigma_i\}$ referenced to create the scenario. Further information used to create the scenario may also be saved, ensuring full recoverability. When planning procedures with rolling horizons

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[42] The current state at the time of planning may be used as a parent scenario, which is denoted as ω_0.

and freeze periods are used, states of nominal scenarios may be marked as frozen, enforcing that alternative scenarios may diverge at the last frozen period at the earliest.

Past states have only limited value for planning. Thus, past states in the DB should be systematically deleted, while retaining the ability to use them for calibration, testing new DSS, and learning with the DSS. Thus, some past states should be kept. The rules for the version thinning process need to consider the specific demands for calibration, testing and learning modes. The relevant information and desired frequency may be captured and formulated as a requirement for each use of past states. With these, the thinning process is designed. When the DB capacity is not a significant issue, a frequency-based approach applied to full states is the most practical solution. In this approach, the frequency of saved states is decreased with increasing distance from the current time.

When the capacity is an issue, a more specific approach considering changes between states for thinning is necessary. To establish a change detection algorithm, different types of changes $\hat{\delta} \in \widehat{\Delta}^{(STATE)}$ need to be defined and weighed in terms of their relevance. Then a particular state y_{t_1} is only kept if the change index $\Delta y_{t_1 \to t_2}^{(STATE)}$ is larger than a chosen change threshold $\overline{\Delta y}^{(STATE)}$.

$$\overline{\Delta y}^{(STATE)} < \Delta \mathrm{y}_{t_1 \to t_2}^{(STATE)} := \sum_{\hat{\delta} \in \widehat{\Delta}^{(STATE)}} w_{\hat{\delta}}^{(SCT)} \left(\Delta \mathrm{y}_{t_1 \to t_2, \hat{\delta}}^{(STATE)} \right)^{\iota^{(SC)}} \qquad \text{Equation 4-12}$$

Where $\Delta y_{t_1 \to t_2, \hat{\delta}}^{(STATE)}$ is the change index for the change type $\hat{\delta}$, $w_{\hat{\delta}}^{(SCT)}$ the corresponding weight with $\sum_{\hat{\delta} \in \widehat{\Delta}^{(STATE)}} w_{\hat{\delta}}^{(SCT)} = 1$, and $\iota^{(SC)}$ an exponent to determine the significance of large single type changes.

For calibration methods that require many states but minimal information, creating partial past states is possible, i.e., states that only include the specific information relevant for calibration. These partial states can then be saved with a higher frequency than the 'normal' states.

4.3.1.6 Multi DSS & Multiuser Integration

In the proposed framework, the DB serves multiple users with different DSS. Multiple users and DSS are allowed to specify information at any time. Therefore, a concept is required to specify the origin of information. Furthermore, this multi-use raises issues regarding data granularity, preprocessing, and access rights.

The granularity of data and periods needs to be adapted to the DSS with the most granular data requirements. Any less granular model must aggregate data according to the aggregation rules described in 4.2.3.3. Information that is more granular than the DM requires should be aggregated using appropriate aggregation rules. Caution is advised when using information for multiple purposes, as some forms of aggregation may be more suitable for certain applications than others.

In a system handling sensitive information, access to that information must be managed appropriately. An access system specifies access to sets of information Υ, based on user roles $\xi_i \in \Xi_\mu$, which users μ may acquire. Any DSS is limited to the user roles of its current user. Information sets are defined through the type of information included, information content, or a combination of both. To minimise the complexity in the DB, the information sets are realised through the scenario versions and scenario spaces. Any role contains a set of permissions, each addressing either specific scenario versions or scenario spaces. Scenario space access can also be limited to nominal or active scenarios. Additionally, access to particular tables can be restricted to ensure that sensitive information is only accessible to authorised users.

4.3.2 Base Level Functions

The following section discusses the functions provided to all application models, aside from the provision of data. These functions mainly concern the validity of the models for the modelled system and the exchange of information between models.

4.3.2.1 Calibration & Validation

Due to the long reconfiguration times and the lack of opportunities to test different network configurations, PNC is a low-feedback environment. This makes the calibration and validation of predictive models challenging. In many cases, only the model's current state is captured in data. Therefore, the only available validation test is to compare model outcomes of the current period to real figures. If done thoroughly, i.e. decomposing outcomes and thus testing contributing factors individually, this procedure may yield reasonably validated static[43] characteristics of the models. The ability to validate is aided by the relatively simple, i.e. linear, nature of PNC models. However, the dynamic

[43] Static herein refers to model predictions made without configuration changes, whereas dynamic refers to predictions made with reconfiguration.

characteristics of such models are often not empirically validated, especially in the case of single-use models. These dynamic characteristics, for example, include the times and costs of reconfiguration and scaling behaviours. Instead of testing the empirical validity of such models against reality, modellers often rely on validating the conceptual model against theory and verifying the executable model (Sargent, 2010). This can, however, lead to issues as some of the relevant parameters are difficult to assess.

As explained in 2.2.3.6, *calibration* and *validation* are related activities, differentiated by the intention pursued. Both compare the output of a model to the outputs of its real equivalent. Whereas calibration seeks to adapt or train the model to better represent reality, validation determines the confidence that can be placed in the model's results. Calibration requires an inverse function to adapt models according to the difference between results, and validation requires a measure to assess the results objectively. As both require data describing the real system's outputs, a similar functionality may be used for both. A major contribution of having a synchronised multi-version DM is the ability to calibrate and validate the dynamic characteristics of models by comparing parameters to multiple versions of the real system through time. In this work, calibration refers to adaptations made to the model that are not directly imported parameters, which are synchronised[44]. This synchronisation is discussed in 4.4.2.1.

In general, three types of calibration are distinguished. (i) *Direct measurement* is the immediate measuring of a parameter and is preferable wherever possible. (ii) *deterministic deduction* utilises a calibration function, $f^{(CAL,DET)}(l) = p$, where l is a measurable tuple of inputs U_l and outputs O_l and p is the parameter to be calibrated[45]. When $f^{(CAL,DET)}$ depends on the system state, p cannot be deduced unambiguously and (iii) *regressive deduction* has to be used. Regressive calibration functions $f^{(CAL,REG)}(L) = p$ use a set of $N_L^{(CAL)}$ input-output tupels to determine the parameters[46]. To facilitate regressive deduction, two sets of sources for L can be used. Spatial data uses multiple instances within the system at which p acts, whereas temporal data uses multiple

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[44] In this sense, calibration refers to the inference of model characteristics that are either not possible or very difficult to measure directly. For example, average machine occupancy per product is easily measurable. The required rate of maintenance personnel per machine is often not recorded and must be inferred or estimated.

[45] Compare 2.2.3.6.

[46] With regressive deduction, Bayesian calibration is possible, though not practical in most circumstances of PNC models. However, for stochastic parameters, those techniques are applicable.

system states and requires those states to be saved accordingly[47]. Calibration services $\lambda_p^{(BMA,CAL)}$ can be developed specifically for each model parameter to be calibrated.

For a first assessment of calibration services, three aspects are considered: (i) *uncertainty*, (ii) *influence*, and (iii) *opportunity*. Uncertainty describes the degree of doubtfulness regarding the parameter. Influence describes the influence the parameter has on model results and the importance of those results. Opportunity describes the availability of suitable data to calibrate the parameter. To compare calibration demands each aspect is expressed as a level on a scale, i.e. $v_p^{(UNC)}, v_p^{(INF)}, v_p^{(OPP)} \in (0,1)$ and the calibration priority $V_p^{(CAL)}$ is expressed as

$$V_p^{(CAL)} = v_p^{(UNC)} v_p^{(INF)} v_p^{(OPP)} \qquad \textit{Equation 4-13}$$

Where higher values of $V_p^{(CAL)}$ signal a higher priority for calibration.

Four different types of calibration scheduling can be implemented depending on the application's requirements and the time necessary for calibration. (i) *On-demand calibration* is performed when specified by the user, (ii) *frequency-based calibration* occurs at predetermined time intervals, (iii) *ex-ante calibration* is performed before every use of the DSS, and (iv) *rule-based calibration* is performed based on observed deviations[48]. An overview of the calibration scheduling types, their benefits and drawbacks, and when to apply each is provided in Table 4-9.

Validation is meant to ensure decisions made with the aid of a model can be trusted. Thus, in validation, parameters are not changed to fit the system's behaviour, but rather the deviation between the modelling results and the system's behaviour is tested. In this work, three types of validation shall be distinguished. (i) *Principal validation* occurs in model development to ensure general validity of the model with the examined system, (ii) *ex-ante validation* is performed before use to ensure the model is suited to the particular case in question, and (iii) *ex-post validation* is performed after model application to ensure the results of an already prepared decision.

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[47] In some cases, dynamic parameters may be able to be deduced deterministically but still require multiple system states as part of the calibration tuple l.

[48] Deviations can be tested according to the scheduling types (i)-(iii). Deviation testing should always be less computationally complex than the calibration.

Table 4-9: Calibration Scheduling Types and Corresponding Considerations

Type	Advantages	Disadvantages	Application
on-demand	• Minimises calibration efforts • Easy to implement	• Calibration is not ensured	• When calibration demands are not critical • When calibration requires much manual input
fre-quency-based	• Reliable calibration age • Planned calibration to avoid capacity collisions	• Major changes may be missed • May cause unnecessary updating • Requires the use of independent calibration programs	• When the use frequency is very reg-ular and predictable • When changes are predictable • When calibration efforts are low
ex-ante	• Ensures model is calibrated • Avoids unused calibration efforts • Relatively easy to implement	• Calibration time is added to deci-sion-making time • May cause additional effort with-out actual changes	• When calibration is critical • When calibration effort is low • When decision time is not critical
rule-based	• Ensures model is sufficiently calibrated • Avoids updating old data	• A deviation detection algorithm is necessary	• When changes are not predictable, but calibration demand is critical • When calibration efforts are high • When changes trigger use • When decision time is critical

4.3.2.2 DSS Interaction Design

Another pertinent issue in the described system with multiple DSS is their interaction. For the interactions, it is assumed that a DSS, which may consist of multiple models, is attributed to a specific decision-making process π. When DSS supports multiple PNC tasks, interdependencies between the decisions and plans of each naturally arise. Depending on the particular organisational setting, different dependencies between the planning processes exist, which need to be supported through the DB and the DSS.

In essence, dependencies amount to one PNC task requiring information from another[49]. This information is created by using the models in specific problem situations. Depending on the framework's development level, different forms of DSS initiation may be employed. The most basic form is *user-based initiation*, where the DSS user creates and solves planning problems with the help of the DSS. In *request-based initiation,* one DSS requests information from another while determining the parameters the other should employ. In *event-based initiation,* DSS subscribe to predetermined changes in the DB and automatically plans, using the newly available data. That data may originate from ISs or other DSS. Finally, *capacity-based initiation* employs the concept of Daydreaming Production, as described by Nassehi et al. (2022), to plan new scenarios

[49] A more thorough discussion of overlapping competencies between decision-making processes and models is provided in 4.2.4.2. Here, only information exchange and realisation of interactions are considered.

whenever spare computing capacity is available. These initialisation forms are symbolically displayed in Figure 4-18 and are discussed in more detail in Benfer et al. (2023).

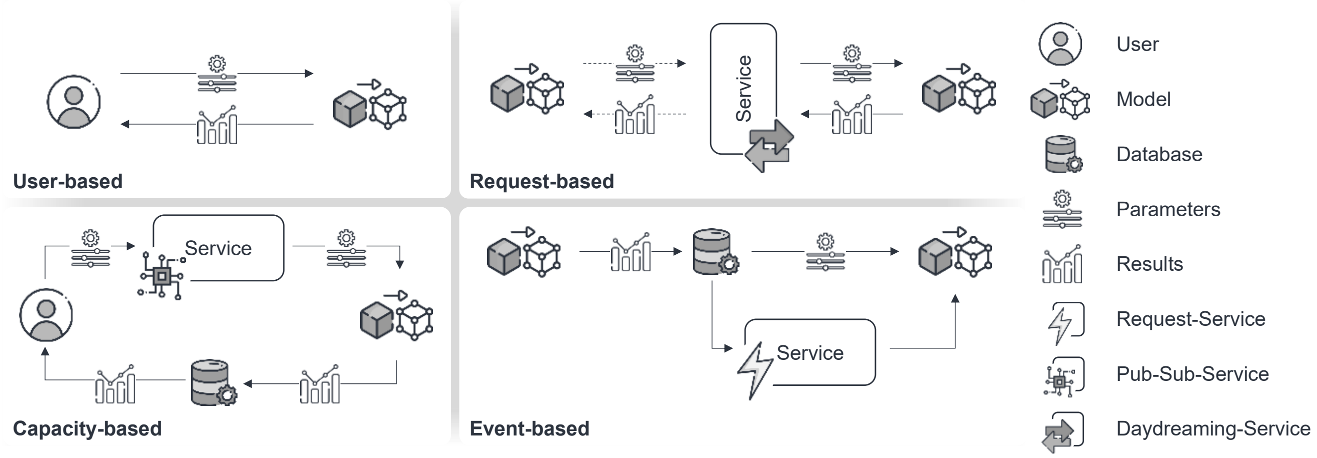

Figure 4-18: Initiation Types Between Multiple DSS

Depending on the initiation form, the relevant parameter space of the DSS needs to be specified. Table 4-10 shows this relation for each of the initiation forms. Different data provision levels are suitable depending on the chosen interaction forms. This issue is discussed in more detail in Benfer et al. (2023).

Table 4-10: DSS Initiation Types and Impacts on Parameter Definition

Initiation Type	Characteristics	Implications for the Model Parameter Definition
User-based	The user initiates model experiments.	Highest flexibility regarding parameter definition.
Request-based	The model provides results as a service that other models may request. The service defines the parametrisation of the response model.	Both model-specific parameters and system parameters need to be specified by the service.
Event-based	New available data, either base data or model results, trigger model execution.	Partial automatic parameter specification is possible.
Capacity-based	Model execution is performed based on the availability of computational resources.	Parameter ranges with probability density functions need to be defined.

4.3.3 Generation & Synchronisation of Application Models

The following section focuses on generating application models. In principle, a DSS defined according to the procedure proposed in 4.2.3, which is connected to the DB discussed previously, can be generated automatically. However, in practical settings, several of the above assumptions due not hold. Typically, some model parameters will not be available automatically. The focal production system[50] may change from application to application. The considered task may change the requirements towards the

[50] In the sense of the part of the production system which the predictive model focuses on (compare 4.2.3.3.2).

DSS. Thus, a model generator is necessary that lets users manipulate the above-discussed aspects and create a DSS according to their preferences.

4.3.3.1 Selection of Adaption Options

The framework presented here assumes that different DSS are suitable for different tasks and should thus be designed and implemented independently. However, developing a new DSS for every PNC task instance is neither practical nor efficient. Thus, any DSS must cover a range of PNC tasks. To adapt DSS to different tasks, some DSS design decisions may be made available to the users, allowing them to adapt a DSS to their specific needs. In principle, this approach could be applied to all DSS design decisions, an idea, for example, pursued by Sager (2018). However, especially the changing aspects of the system that are determined in phases one and two of the DSS design process, introduced in 4.2.3, require considerable changes to a DSS, thereby increasing the complexity of the solution. Thus, this work suggests that only decisions made in Phase 3 should be considered for implementation as DSS adaptations[51].

At its core, this includes three types of decisions: (i) *abstraction level*, (ii) *functional representation*, and (iii) *delimitation*, each of which is discussed in more detail in the subsequent sections. In general, the range of tasks a DSS applies to encompasses the range of different tasks in terms of objectives, time horizon, and other factors, as well as the range of equivalent systems that the DSS may represent. Depending on these ranges and the resulting differences in DSS design, different adaption choices $\hat{\gamma} \in \hat{\Gamma}_m$ with a set of possible adaption options $\gamma \in \Gamma_{\hat{\gamma}}$ are available.

To this end, an application portfolio for a DSS can be designed, describing the various tasks and the range of applications, as well as the changes in requirements and restrictions associated with these different application forms. For each differing design decision, an adaption option may be created. Different options may pose specific requirements towards the available data or require additional computational capabilities. To ensure that the necessary data is available, the most comprehensive option is assumed to be the original version of the model. An example of adaptation options structured as a morphological box is shown in Figure 4-19. It shows the three types of DSS

[51] For example, a change in AC level through the inclusion or exclusion of decision variables in the prescriptive subject set $X^{(SUB,PSC)}$ would not be implemented as an adaption option but rather as a separate DSS. While it can be possible to allow methodological changes, these are not explicitly considered here.

specifications introduced in 4.2.3.3.2, alongside their corresponding options. For example, production orders can be distinguished by customer, delivery location, and or product variant. These discriminations themselves can be instance-specific, based on instance clusters or left out. Similarly, material costs can be modelled as linear, degressive, or contract based. Delimitation describes the selection of the focal system. For example, users may choose only to include elements from Site A, B, and D, as well as regions 1 and 4.

Abstraction	Production Order	Customer	None	Specific				
		Delivery Location	None	Clustered	Specific			
		Product Variant	None	Clustered	Specific			
Functional Represen-tation	Material Costs		Linear	Degressive	Contract-based			
	Depreciation Costs		Linear, infinte	Linear, finite	Degressive			
	Equipment Efficiency		Average, fixed	Dynamic improvement	Condition specific			
Delimitation	Markets		Region 1	Region 2	Region 3	Region 4		
	Production Steps		Final Assembly	Preassembly	Component Production			
	Sites		Site A	Site B	Site C	Site D	Site E	Site F

Figure 4-19: Exemplary Adaption Option Portfolio

It is advisable to perform this adaption option analysis at the beginning of the DSS implementation. Still, an iterative process is usually necessary, as different tasks may only be recognised when using the DSS, and differences between equivalent systems may only be uncovered through close examination of their representation in the DSS. For adaptation options that require an elaborate adaptation of the DSS itself or that increase the complexity of the resulting DSS too much, a forking of the DSS into two different DSS is a viable option. Whether a DSS should be managed as one application with adaption features or multiple distinct DSS for various purposes should be made on a case-by-case basis. While DSS for planning tasks have been considered so far, other types of uses are also conceivable. Those are discussed in 4.5.1. The presented adaption options can also be used for those.

4.3.3.2 Abstraction Level Adaption

The selection of different abstraction levels is predicated on the equivalent behaviour of system elements at different abstraction levels. This equivalence is dependent on the model m and the element e, and the abstraction needs to be designed in recognition of this equivalence. For example, when modelling production capacity when the period length $\Delta\theta^{(PER)}$ is magnitudes higher than the production lead time $\Delta\theta^{(LT,PROD)}$, a cluster of individual milling machines $r \in R$ with capacities q_r may be reasonably abstracted by one aggregate machine $r_R^{(ABS)}$ with the capacity $q_{r_R^{(ABS)}} = \sum_{r \in R} q_r$.

However, in a model that estimates lead times under the assumption that one product is always allocated to one machine at a time, a different type of abstraction must be chosen, and differences in the effects on model accuracy may occur. This example shows the two general forms of abstraction: (i) abstraction as aggregation, where multiple elements are unified into one larger element and (ii) abstraction as representation, where a generalised form with unified characteristics represents multiple elements. Depending on the form of abstraction, a suitable abstraction function $f_{\hat{h}}^{(ABS)}$ for each of the property $\hat{h} \in \widehat{\mathrm{H}}_{\hat{e}}$ of a particular element type $\hat{e}$ can be specified.

Every adaptation option should be focused on a specific choice the user may make. In this work, the starting point for the abstraction level of each element type is determined by the original model according to 4.2.3.3.2. For abstraction, this means the user can specify an abstraction criterion which is used in the original model, which should not be applied to a specific focal element type $\hat{e}_{\hat{\gamma}}^{(FOCAL)}$. However, as the choice of abstraction level may influence the abstraction level for other element types, a set of element types $\hat{\mathrm{E}}_{\hat{\gamma}}^{(ABS)}$ affected by $\hat{\gamma}$ is identified[52]. The abstraction function $f_{\gamma}^{(ABS)}: \widehat{\mathrm{H}}_{\hat{\gamma}}^{(ORG)} \rightarrow \widehat{\mathrm{H}}_{\gamma}^{(ADP)}$ of each $\gamma \in \Gamma_{\hat{\gamma}}$ then maps the set of properties $\widehat{\mathrm{H}}_{\hat{\gamma}}^{(ORG)} = \left(\widehat{\mathrm{H}}_{\hat{e}} \,\middle|\, \hat{e} \in \hat{\mathrm{E}}_{\hat{\gamma}}^{(ABS)}\right)$ before the abstraction to the set of abstracted property types $\widehat{\mathrm{H}}_{\gamma}^{(ADP)}$.

When the set of elements for multiple adaptation options intersects, a combined abstraction function must be defined, which typically resembles the sequential application of the individual abstraction functions.

4.3.3.3 Model Expression Adaption

Changes in the model expression may significantly alter the accuracy and data demands of the model. These changes may be necessary to account for differences between the modelled systems. For example, production systems with very large items

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[52] This set will typically be smaller than is usually the case when using the original approach proposed by Benfer et al (2019), as the dependencies between model elements normally enforce a minimum level of detail and rarely a maximum level of detail.

may have significantly different transport cost functions compared to smaller items, which could be shared in a container. To implement an adaption option in a model, the option needs to be parameterised. This parameter may be determined at runtime or during model setup. The former is easier to implement, but the latter is more computationally efficient. Data demands for each functional adaption option need to be checked.

4.3.3.4 Focal System Delimitation

As specified in 4.2.3.3.2, the focal system is defined along several dimensions, representing different functional aspects of the overall production system in the form of domains or elements within the DM, such as products, processes, markets, etc. In cases where different domains are to be included or excluded, functional adaptation options must be utilised. For all other dimensions, a procedure is necessary to define the set of entities that comprise the model. A delimitation adaption choice $\hat{\gamma}$ determines a selection element type $\hat{e}_{\hat{\gamma}}^{(SEL)}$ such that a set of selected elements $E_{\hat{e}_{\hat{\gamma}}^{(SEL)},\gamma}^{(SEL)}$ may be chosen by the user. Then the focal set $E_{\gamma,m}^{(FOCAL)}$ of the model m includes all elements with a directed connection to any element in $E_{\hat{e}_{\hat{\gamma}}^{(SEL)},\gamma}^{(SEL)}$ [53]. When multiple delimitation adaption choices $\hat{\gamma} \in \hat{\Gamma}^{(DEL)}$ are present and the chosen option for each $\hat{\gamma}$ is denoted as $\gamma_{\hat{\gamma}}$ the set of elements $E_m^{(FOCAL)}$ in the model is defined as $E_m^{(FOCAL)} = \bigcap_{\hat{\gamma} \in \hat{\Gamma}^{(DEL)}} E_{\gamma_{\hat{\gamma}},m}^{(FOCAL)}$.

As discussed in 4.2.3.3.2, segmenting a system into a part that is in scope and one that is out of scope requires the creation of replacement elements that replace out-of-scope element interactions with the in-scope system. Fundamentally, replacement elements may be created for every interaction $f_{\hat{e}_1,\hat{e}_2}^{(INT)}$ between two element types $\hat{e}_1, \hat{e}_2 \in \hat{E}_m$ in the model. A replacement element $e_{e,f_{\hat{e}_1,\hat{e}_2}^{(INT)}}^{(REP)}$ of type $\hat{e}_2$, with respect to $f_{\hat{e}_1,\hat{e}_2}^{(INT)}$ and an element e of type $\hat{e}_1$, that represents a set of out-of-scope elements $E_{\hat{e}_2,e,f_{\hat{e}_1,\hat{e}_2}^{(INT)}}^{(OOS)}$ than needs to fulfil:

[53] Note that this may include elements of type $\hat{e}_{\hat{\gamma}}^{(SEL)}$ which are not part of $E_{\hat{e}_{\hat{\gamma}}^{(SEL)},\gamma}^{(SEL)}$ as there may be selfreferencial relations in the DM. For example, products may serve as components of other products. However, the directionality condition excludes elements which only share the same type of connection to an element outside $E_{\hat{e}_{\hat{\gamma}}^{(SEL)},\gamma}^{(SEL)}$, e.g. products that share components with the selected products are not part of the model.

$$f^{(INT)}_{\hat{e}_1,\hat{e}_2}\left(e, E^{(IS)}_{\hat{e}_2,e,f^{(INT)}_{\hat{e}_1,\hat{e}_2}} \cup E^{(OOS)}_{\hat{e}_2,e,f^{(INT)}_{\hat{e}_1,\hat{e}_2}}\right) \cong f^{(INT)}_{\hat{e}_1,\hat{e}_2}\left(e, E^{(IS)}_{\hat{e}_2,e,f^{(INT)}_{\hat{e}_1,\hat{e}_2}} \cup e^{(REP)}_{e,f^{(INT)}_{\hat{e}_1,\hat{e}_2}}\right) \qquad \textit{Equation 4-14}$$

where $E^{(IS)}_{\hat{e}_2,e,f^{(INT)}_{\hat{e}_1,\hat{e}_2}}$ denotes the set of relevant in scope elements of type $\hat{e}_2$. Following this, replacement definition functions $f^{(REP)}_{f^{(INT)}_{\hat{e}_1,\hat{e}_2},\hat{e}_2}$ need to be specified for each $f^{(REP)}_{f^{(INT)}_{\hat{e}_1,\hat{e}_2},\hat{e}_2}$ and $\hat{e}_2$[54].

4.4 Data Acquisition

Several data points need to be acquired to enable the DSS and base-level functions outlined in the previous chapters. This acquisition must ensure data quality while remaining economically viable. This chapter addresses this need and PRQ3:

How can the data acquisition for DSSs for the configuration of GPN be realised with low effort and suitable automation?

Data can be acquired from several different data sources, which are described and analysed in 4.4.1. To ensure adequate data quality and expand the amount of available data, different acquisition strategies are systematised in 4.4.2. Finally, costs and benefits associated with the acquisition strategies are assessed in 4.4.3. Figure 4-20 provides an overview of this structure.

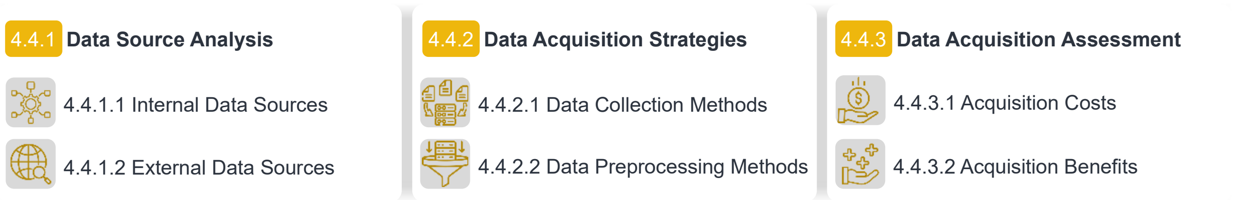

Figure 4-20: Overview of Section 4.4 – Data Acquisition

4.4.1 Data Source Analysis

In this first section, the sources for data used in this work are identified and characterised to form a data source catalogue. A data source is a system or process which may be accessed to retrieve data characterising the current system and its environment. To develop a data source catalogue for PNC tasks, first, relevant IS and other data sources are collected and characterised. Data sources can be distinguished into internal data sources, primarily accessible by the focal organisation, and external data sources,

[54] These replacement definition functions can often be relatively simple, e.g., area demand of out-of-scope products at a site, but may also be quite complex, e.g., replacement production orders that affect set-up times on in-scope resources.

which the organisation can access. The former are primarily relevant to describe the production network, while the latter are particularly relevant for external influences.

4.4.1.1 Internal Data Sources

Internal data sources may be (i) the ISs the organisation operates, which keep data in a structured form, or (ii) proprietary, usually file-based systems or data warehouses, which store data in semi-structured form. The proprietary systems differ by organisation and may even vary within one organisation. Thus, they cannot be characterised without a specific organisation. ISs also vary by organisation but follow a set of specifications or norms that extend beyond single organisations. An overview of relevant ISs, including their original primary purpose, focal domains, and examples for the available data relevant for PNC tasks, is given in Table 4-11.

Table 4-11: Overview of Information Systems as Internal Data Sources

Internal Data Source	Primary Purpose	Focal Domains	Exemplary Data Provided
ERP	Comprehensive planning, coordination, and management of company-wide tasks.	All	Master Data for: Sites, Suppliers, Production Resources, Product Variants, Customers, Tools, Status Data for: Personnel, Inventory, Transaction Data for: Order Processing, Production Volumes,
SCM	Planning, coordinating, and managing the supply chain, concerning suppliers, inventories, and logistics.	Procurement & Supplier Management, Logistics	Supplier Master Data, Transaction and Status Data for Procurement, Logistics
MES	Collection, processing, and storage of shopfloor data for production system control and scheduling.	Production	Transaction Data for Machine Utilisation, Process Times, Failure Rate, Process Sequences
APS	Supply chain planning and control with higher analytical capability.	Production, Procurement & Supplier Management	Planning Data for Supplier Deliveries, Logistics, Production
PDM/ PLM	Management of product-related information.	Product Design	Product Architecture & Portfolio, Bill of Materials
CRM	Management of customer-related information and processes.	Sales, Customer Service	Master Data for Customers, Sales Forecasts,
CAQ	Management of quality-related information and processes.	Quality Management & Control	Production Technologies, Tools, Releases & Certifications,

Within the IS, multiple data types are stored, each of which may be assessed regarding the available data quality and accessibility. The design of data acquisition strategies and their assessment are briefly discussed in 4.4.2 and 4.4.3.

4.4.1.2 External Data Sources

A range of external data sources exists that organisations can tap into to improve their models. These data sources principally concern external influences on PNC. Thus, they are not relevant for every PNC task but for those involving external influences. Table

4-12 provides a non-exhaustive overview of relevant sources that may be integrated into an instantiation of the framework.

Table 4-12: Overview of External Data Sources and Relation to External Influences

External Influence	Relevant External Sources	Description
Markets	Economic Trends	Market observations, trends, and forecasts
	Customer Surveys	Surveys on customer preferences
	Patent Databases	Patents granted for relevant technologies
Cost Factors	Trading Prices for Materials	Trading prices for relevant materials
	Economic Figures	Overall economic figures, inflation, cost of capital
	Worker Availabilities	Regional employment figures
	Energy Costs	Regional market prices for several types of energy
	Labour Costs	Costs for personnel by region and sector
	Emission Catalogues	Catalogues associating average emissions with typical parts
Logistics	Logistic Cost	Transport/logistics rates for available routes
	Logistic Monitoring	Status monitoring portals for shipment
	Disruption Monitoring	Monitors for regional disruptions affecting suppliers
Cultural Factors	Local Education Levels	Level of education of the local population
	Employee Turnover	Average local employee turnover in the comparable sector
Legal Factors	Trade Policy Database	Overview of duties and other import policies
	Legal Security	Rule of law indices
Political Factors	Political Stability	Political stability indices

4.4.2 Data Acquisition Strategies

Whereas the previous section focused on data origins, this section focuses on establishing data acquisition strategies to satisfy the data demands specified following 4.2.3.3.3. Such strategies provide the data for a set of data demands and thus elements or properties in the DB. The strategy consists of a data collection method describing how data is accessed and a set of data preprocessing methods that transform the data according to the requirements of the PNC models. The section is in part based on the works of A_Uber (2021) and A_Brache (2022), which were supervised by the author.

4.4.2.1 Data Collection Methods

To describe and distinguish methods for data collection, the possible situations concerning the desired data must be defined. This framework distinguishes methods suitable for the following situations: (i) No expressed information[55] is available and data collection is infeasible, (ii) no expressed information is available but data collection is

[55] Here, expressed information is understood as information that is represented in a shareable form. By contrast, much knowledge about production networks is implicit and requires additional steps to share or may even be unconscious and thereby inaccessible to elicitation.

feasible, (iii) expressed information is available in unstructured form, and (iv) expressed information is available in a structured form.

For (i), the data needs to be estimated by humans. *Estimation methods* range from single expert point predictions to combined predictive densities (McAndrew, & Wattanachit et al., 2021, pp. 3–5). Depending on the type of required data, the availability of experts, and desired time and effort, different questioning, interaction, and combination methods can be used (Hanea, & Hemming et al., 2022). Estimation methods can, for example, be used to assess future market developments, the likelihood of disruptions, or required production times for engineer-to-order products. As the effort for each estimation is high, these methods should be limited to data that only needs to be updated seldom.

In case (ii), *data recording* needs to be established. Industrial data recording techniques may be manual, semi-automatic, or automatic (Ćwikła, 2013, p. 619). In most circumstances, automatic data recording is preferable to manual data recording in terms of accuracy and speed, but it requires larger initial investments. Depending on the circumstances, various data recording methods may be employed. Often, data captured is relevant beyond PNC tasks and should be stored primarily in an adequate IS. In that case, additional costs may be incurred, but further benefits of data availability may also occur.

For (iii), *structuring methods* that make data accessible to models are required. Structuring can involve transforming files with individual non-formalised data structures or interpreting and mapping keywords across multiple contexts. Due to the non-formalised nature, errors in the source data and structuring are common, but can be addressed by the preprocessing methods described in the next section.

For (iv), *interfaces* between IS and the DB need to be established. The interfaces of many IS are proprietary, limiting content and form of access. Access rights of the ISs also need to be taken into consideration.

In any of the four cases, the synchronisation type, with which data is updated in the data base is an essential factor. The required frequency depends primarily on the dynamism of the decisions for which a company wants to use it (Townsend, & Le Quoc et al., 2018, p. 428). Synchronisation may be conducted *on demand*, *frequency-based*, or *change-based*. Table 4-13 provides an overview of these synchronisation types and their advantages, disadvantages, and ideal applications. The synchronisation type can be chosen for each data acquisition strategy in this framework.

Table 4-13: Comparison of Different Synchronisation Types

Type	Advantages	Disadvantages	Application
on-demand	• Ensures data is updated • Avoids "unused" data updates	• Synchronisation time is added to decision-making time • May cause additional effort without actual changes	• When the use frequency is much lower than the change frequency • When decision-making time is not critical
frequency-based	• Reliable data age • Planned synchronisation avoiding capacity collisions • Easy to set up	• Major changes may be missed • May cause unnecessary updating	• When the use frequency is very regular and predictable • When synchronisation costs are low
change-based	• Ensures data is updated • Avoids updating old data	• A change detection algorithm is necessary • May produce many unused updates	• When the average change frequency is much lower than the use frequency • When synchronisation costs are high • When changes trigger use • When decision-making time is critical

4.4.2.2 Data Preprocessing Methods

In many cases, data is not immediately available in the desired format or the desired quality. Thus, this work uses a three-step approach to data preprocessing consisting of (i) *cleaning*, (ii) *data integration*, and (iii) *transformation*, adapted from García et al. (2015, pp. 39–40) and Han et al. (2023, pp. 2–3). Table 4-14 presents a catalogue of data preprocessing methods structured by the preprocessing step.

Data cleaning refers to all activities intended to filter out incorrect information. Data integration involves assembling data from various sources, each with its own schema and identity. Data transformation refers to all methods involved in adapting data to the target schema, as well as reducing and abstracting it. Different methods are suitable depending on the type of data and the expected volume, as defined by the synchronisation frequency. A more detailed description of the methods is offered in Appendix A4.2. The methods can be added to data acquisition strategies, provided they fulfil the respective selection criteria.

A complete data acquisition strategy is formed in conjunction with the corresponding preprocessing methods. As multiple strategies may be suitable for the same data source and information, alternative candidates may be designed to be assessed based on the methodology described in 4.4.

Table 4-14: Preprocessing Strategies According to García et al. (2015) and Han et al. (2023)

Steps	Categories	Description	Variants
Cleaning	Imputation	Dealing with missing values in data sets.	Discard, expectation maximisation, multiple imputation, Bayesian principal component analysis, K-nearest neighbour, K-means clustering imputation, support vector machine imputation, local least squares imputation, hot-deck imputation
	Noise Reduction	Identifying and removing noise from data.	Ensemble filter, cross-validated committees filter, iterative portioning filter
Data Integration	Schema Matching	Translation of data from one schema to another.	Rule-based, label-based, instance-based, structure-based, embeddings
	Redundancy Elimination	Identification and elimination of redundant data.	Chi-squared correlation, Pearson correlation, cosine-similarity, edit distance, Jaro, token-based similarity, Bayesian decision rules, support vector machines, clustering
Transformation	Normalisation	Transforming data to a normalised scale.	Min-max normalisation, z-score normalisation,
	Advanced Transformation	Transformations to create new, more suitable attributes.	Linear transformation, quadratic transformation, polynomial approximation, non-polynomial approximation, rank transformation, Box-Cox transformation, nominal-to-binary transformation, encodings, embeddings
	Dimensionality Reduction	Reducing the dimensions of data taken into account.	Principal component analysis, factor analysis, multidimensional scaling, clustering, local linear embedding
	Discretisation	Transforming continuous attributes into discretised attributes.	Information-based, statistical, rough sets, wrappers, binning

4.4.3 Data Acquisition Assessment

In this section, the data acquisition strategy candidates determined according to the previous section are assessed regarding the associated costs and benefits to the organisation, applying a range of DSS.

4.4.3.1 Acquisition Costs

The costs $C_{\lambda_d^{(DAS)}}$ of a data acquisition strategy $\lambda_d^{(DAS)}$ are composed of the expenses for set-up $C_{\lambda_d^{(DAS)}}^{(SU)}$ and the fixed and variable operating expenses $c_{\lambda_d^{(DAS)}}^{(FO)}$ and $c_{\lambda_d^{(DAS)}}^{(VO)}$ respectively. With $N_{\lambda_d^{(DAS)}}^{(SYNC)}(\theta)$, denoting the number of synchronisations at θ follows:

$$C_{\lambda_d^{(DAS)}}(\theta) = C_{\lambda_d^{(DAS)}}^{(SU)} + c_{\lambda_d^{(DAS)}}^{(FO)}\theta + c_{\lambda_d^{(DAS)}}^{(VO)} N_{\lambda_d^{(DAS)}}^{(SYNC)}(\theta) \qquad \textit{Equation 4-15}$$

These costs must be estimated based on experience or by decomposing necessary tasks. The work breakdown structure discussed in 2.2.5.2 is a suitable approach for this estimation. The setup expenses are typically determined by software and possibly hardware investments, and necessary development efforts are limited by available development capacity. Assuming the efforts can be freely divided and parallelised, the time required for development can be estimated as the necessary development duration divided by the available capacity.

4.4.3.2 Acquisition Benefits

The benefits of a data source acquisition strategy can only be expressed in terms of their contribution to model applications. Each application may require information that the acquisition strategy provides and thus have a dependency that one or multiple acquisition strategies fulfil. Dependencies specify the quality of provided data and the speed of provision. They can be (i) categorical, i.e. an application can only be realised if a dependence is fulfilled, or (ii) enhancing, if the satisfaction of a dependence improves the application. These dependencies are discussed in more detail in 4.5.2.4.

As discussed in 2.3.1, data quality may be assessed in (i) *accuracy*, (ii) *timeliness*, (iii) *consistency*, (iv) *completeness*, (v) *believability*, and (vi) *interpretability*[56]. The speed of data provision can be expressed in terms of the average necessary time and the variance. Table 4-15 proposes assessment scales for each criterion.

Table 4-15: Assessment Scales for Data Quality and Acquisition Speed

Criterion		Description	Assessment Scales
Data Quality	Accuracy	Degree of agreement with real values	Error frequency, mean-squared error
	Timeliness	Degree to which data is up to date	Ratio of update frequency and change frequency
	Consistency	Degree of formatting and structure uniformity	Frequency of violations of referential integrity
	Completeness	Degree of comprehensiveness and absence of missing data	Frequency of missing values
	Believability	User trust in data	Lickert scale for believability by relevant users
	Interpretability	Ease of data understanding for users	Lickert scale for interpretability by relevant users
Acquisition Speed	Average Acquisition Time	Average time between data demand determination and fulfilment	Mean time
	Acquisition Time Variance	Variance in time between data demand determination and fulfilment	Variance

Categorical dependencies specify a set of requirement levels $v_g^{(DD,RL)}$ of a criterion g, that data acquisition strategies have to fulfil. Enhancing dependencies describe the realised benefits $B_a^{(BT)}$ for an application a in terms of the satisfaction degree of the criteria. A general version of this relation is:

[56] It may not be necessary to assess all criteria in every case. Instead, only relevant criteria should be chosen to minimise the assessment effort. For example, interpretability may not be a concern when capturing machine occupancy and could thus be omitted from the assessment.

$$B_a^{(BT)} = \left[\sum_{d\in D_a} w_d^{(BEN)} \left[\sum_{g\in G_d^{(DD)}} w_g^{(DDB)} \left(\frac{\tilde{v}_g^{(DD)} - v_g^{(DD,RL)}}{v_g^{(DD,SL)} - v_g^{(DD,RL)}} \right)^{\iota^{(CRI)}} \right]^{\frac{\iota^{(DD)}}{\iota^{(CRI)}}} \right]^{\frac{1}{\iota^{(DD)}}} \qquad \textit{Equation 4-16}$$

with $\tilde{v}_g^{(DD)} = \min\left(v_g^{(DD)}, v_g^{(DD,SL)}\right)$ where $v_g^{(DD)}$ is the achieved performance, and $v_g^{(DD,SL)}$ is the satisfaction level, $\sum_{d\in D_a} w_d^{(BEN)} = 1 \forall B_a^{(BT)}$ where d is a data demand and $w_d^{(BEN)}$ the associated normalised weight with respect to $B_a^{(BT)}$, and $\sum_{g\in G_d^{(DD)}} w_g^{(DDB)} = 1 \forall d \in D_a$, where $w_g^{(DDB)}$ is the normalised weight of g with respect to d. $\iota^{(CRI)}$ denotes the type of norm used to weigh criteria and $\iota^{(DD)}$ denotes the norm used to weigh data demands.

Based on this, the utility of a given data acquisition strategy can only be assessed concerning a specific set of existing or planned applications a. Therefore, the decision between data acquisition strategies may only be made when considering the entire application portfolio, which is discussed in 4.5.2.

4.5 Organisational Integration

A DT of GPN may only be successful if it addresses the specific requirements of the focal organisation. The production system characteristics, business processes and organisational culture shape these requirements. This chapter outlines a systematic approach to this problem and thereby addresses PRQ4:

How can such systems be integrated into organisations to optimise their decision-making speed and quality?

Figure 4-21 portrays this chapter's structure.

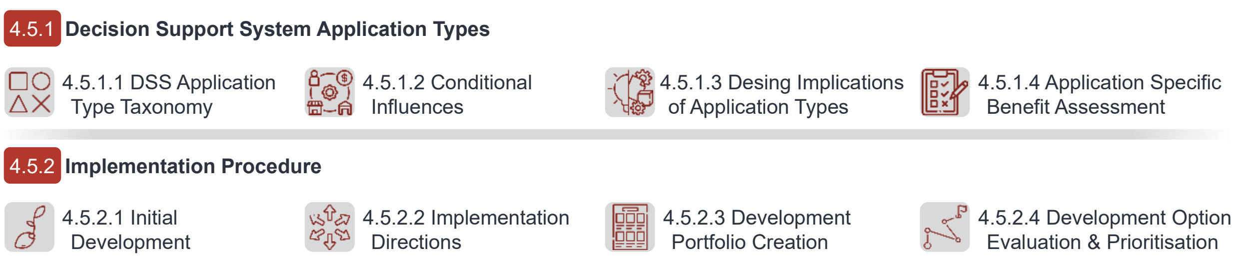

Figure 4-21: Overview of Section 4.5 – Organisational Integration

First, 4.5.1 broadens the scope of application for DSS to additional applications and analyses factors influencing the suitability of these application types. With these additional application types, 4.5.2 proposes a development procedure for the presented DT of GPN.

4.5.1 DSS Application Types

In this section, a taxonomy of application types extending beyond the previously considered planning types is developed and analysed in terms of its interaction with contextual factors, implications for the design of DSS, and organisational benefits.

4.5.1.1 DSS Application Type Taxonomy

Although the previous sections have focused primarily on DSS intended to support planning processes that lead to specific actions, other application types (AT) for DSS are conceivable and may add additional value to organisations. A categorisation of different ATs is developed based on the work A_Krippner (2022) supervised by the author as shown in Figure 4-22.

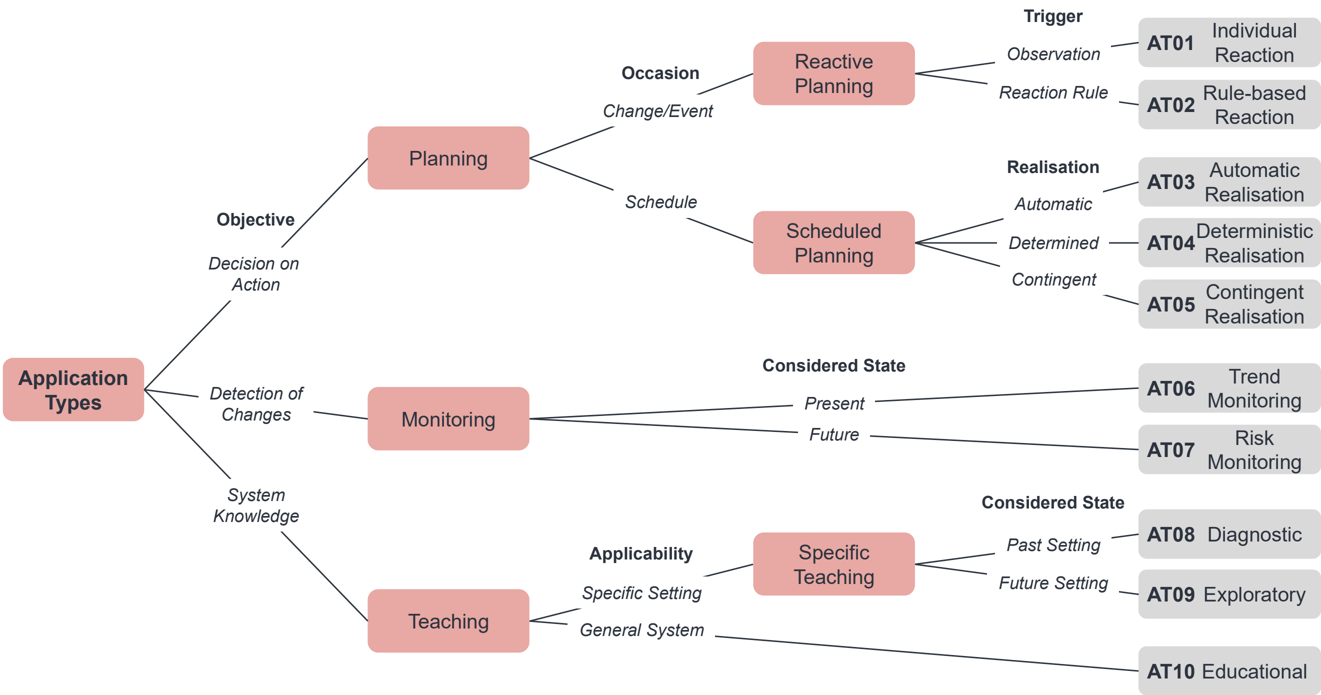

Figure 4-22: Categorisation of DSS Applications in PNC

The principal distinction is made between (i) *planning*, (ii) *monitoring,* and (iii) *teaching* applications. In planning, users aim to determine the most suitable course of action. These applications exemplify the decision support discussed throughout 4.2. In monitoring, users try to detect meaningful changes to the system or its environment which warrant action. Teaching applications are designed to improve users' understanding without pursuing a specified decision. Planning applications can be further distinguished into *reactive* and *scheduled planning* according to the intentionality of the planning process. Monitoring applications can consider present *trends* or search in possible futures for *risks*. Learning applications may be further differentiated by the learning subject into *specific teaching* about past or future states and general *educational* applications that further the user's understanding of the system. Some additional differentiations are possible, as shown in Figure 4-22. A more comprehensive description of the application types is provided in Appendix A5.2. These categories can be supported using the same DSS but emphasise requirements towards the DSS and the DB differently. Furthermore, the benefits of each AT need to be estimated differently. Relevant benefits are introduced in Appendix A5.1. A detailed reflection on the benefit-related differences of ATs is provided in Appendix A5.2.

4.5.1.2 Conditional Influences of Decision Situations

Several influences shape the attractiveness of the above-discussed ATs. These influences are connected to the decision situation characteristics (DC) introduced in 4.2.1.3. Table 4-16 provides an overview of the influences on the application types.

Table 4-16: Conditional Influences on Application Types

Conditional Influences		**AT01**	**AT02**	**AT03**	**AT04**	**AT05**	**AT06**	**AT07**	**AT08**	**AT09**	**AT10**
DC01	System Linearity			++	+	+	+				
DC02	Number of Decision Variables		+	++	+	+	+				
DC03	System Expertise	+	+		+	+				++	-
DC04	Uncertainty					++	++	++		++	
DC05	Decision Frequency		+	++	++	++				+	
DC06	Decision Routine		+	++	+	+	+				
DC07	Development Capabilities		+	++	+	+	++	++	++	++	++
DC08	Perspective Diversity	+	+			+			+	++	++
DC09	Achievable Accuracy			++	+	+	+	+	+	+	
DC10	Objective Quantifiability	+	+	++	+	+	++	+			
DC11	Data Acquisition Intensity			-			-	-	-	-	
DC12	Time Horizon	+	+	--		+		+		+	
DC13	Decision Time	-	-	++	+	+	+	+		+	
DC14	Computing Capabilities			++	+	++	++	++		++	
DC15	Desired Explainability	+	+	-	+	+			++	++	++
DC16	Model Expertise	+	+		+	++	+	+	+	+	

The effect of an increase in a DC on the attractiveness of an AT is evaluated from '--' negative to '++' positive. These assignments are discussed in Appendix A5.2. The influences should be considered when deciding which applications to focus on and assessing the benefits an application type may provide.

4.5.1.3 Design Implications of Application Types

The choice of different DSS application types comes with design implications for the DSS. These implications may affect all aspects of DSS, including the AC, interpretability, the validity scope of a model, parameterisation freedom, interface simplicity, and the importance of automatic data provision. An overview of the implications is provided in Table 4-17. The implications should be considered depending on the specific development situation, i.e., development of a new application as a novel DSS or a change of an existing DSS. Empty fields represent no strong implication.

Table 4-17: Overview of Design Implications of Different Application Types

Application Type		Analytical Capability	Interpretability	Broad Validity	Parametrisation Freedom	Interface Simplicity	Automatic Data Provision
AT01	Individual Reaction	-	+	+	+	-	-
AT02	Rule-based Reaction		+				
AT03	Automatic Realisation	++		-	-	+	++
AT04	Deterministic Realisation	+		-			
AT05	Contingent Realisation	+		-			+
AT06	Trend Monitoring			-	-		++
AT07	Risk Monitoring			-	-		++
AT08	Diagnostic	-	+	+	+	+	+
AT09	Explorative	-	+	+	+	+	+
AT10	Educational		+	+		+	+

4.5.1.4 Application Benefits

The consideration of potential benefits is an essential aspect of application selection. The DSS, the particular PNC tasks, the existing process, the system, its environment, and the chosen application type shape the achievable benefits. According to the literature, several benefits can be achieved through DSS. They can be used as evaluation criteria by assessing the importance of each to the organisation. Table 4-18 shows a selection of benefits based on the discussion in 2.2.5.2 and the application type that may contribute to the benefit, i.e., be relevant. Here, relevance is marked with x, and limited relevance is marked with (x).

Table 4-18: Confusion Matrix for Benefits and Application Types

Benefits		Description	AT 01	AT 02	AT 03	AT 04	AT 05	AT 06	AT 07	AT 08	AT 09	AT 10
BE01	Capital Value	Total economic value of the DSS, with regard to invested and saved resources.	x	x	x	x	x	x	x	x	x	x
BE02	Decision Quality	Expected improvements in decision quality in terms of the organisation’s objectives multiplied by decision frequency.	x	x	(x)	x	(x)	(x)	(x)			
BE03	Decision Speed	Decreases in time to make a decision.	(x)	x	x	x	x	(x)	(x)			
BE04	Decision Transparency	Degree to which decisions are more traceable.	(x)	(x)	x	(x)	x	x	x	x	x	x
BE05	Reaction Speed	Decreases in the speed of addressing unforeseen events.		x	(x)		x	x	x		(x)	
BE06	User System Knowledge	Knowledge users and affiliated persons have regarding the system.	(x)							x	x	x
BE07	Task Learning Speed	Time users need to be able to perform the PNC tasks	(x)	(x)		(x)	(x)	(x)	(x)	(x)	x	x
BE08	User Satisfaction	Contentedness of users with their task.	x	x	x	x	x	x	x	x	x	x
BE09	User Capacity	Available capacity of users for other problems	x	x	(x)	x	x	(x)	(x)	(x)	(x)	

4.5.2 Implementation Procedure

The following describes a systematic implementation procedure for DTs of GPNs. The procedure commences with an initial development phase, where a particular DSS is used as the seed from which the DT is created. After this initial phase outlined in 4.5.2.1, the principal development directions for the DT are categorised in 4.5.2.2. 4.5.2.3 derives a process to systematically identify potential development options and create a development portfolio based on those directions. Finally, 4.5.2.4 introduces an evaluation and prioritisation method for development options that balances long and short-term value.

4.5.2.1 Initial Development

The developed approach to create a DT of an organisation's GPN aims to maximise the value provided to said organisation. It assumes that development resources are limited and intraorganisational trust and conviction towards model-based decision-making must be built over time. As alluded to before, a monolithic implementation is unlikely to succeed under these circumstances, as it would require a very large initial investment, the implementation would require a long time, and benefits realised late could not contribute towards creating organisational momentum. Instead, this work proposes an organic process in which an initial model-based DSS serves as the nucleus for the broader DT. From this initial DSS, several development directions emerge, forming a portfolio of development options described in 4.5.2.2 and 4.5.2.3.

The selection of the initial DSS is crucial for the success of the overall DT. Depending on the individual circumstances, this selection can differ from organisation to organisation. Factors in this selection can be divided into *PNC task* and *opportunity*-based factors. PNC task factors are determined by the suitability of the PNC task under the circumstances of the employing organisation. These factors are largely stable and relate to the DCs. Opportunity-based factors occur as part of the dynamic behaviour of the organisation. They are volatile and should be considered when the selection is imminent. An overview of the relevant criteria is given in Table 4-19.

Table 4-19: Selection Criteria for an Initial DSS

Type	Criterion	Description	Effect
PNC Task	Result Improvement Potential	Degree to which preventable human errors negatively influence the decision process quality.	Increased DSS impact on decision quality.
	Process Improvement Potential	Degree to which a model could reduce decision-making time and effort.	Increased DSS impact on decision-making speed and efficiency.
	Data Requirements	Amount of data from distinct sources required for the decision.	Increased effort to create DSS.
	Scalability	Degree to which similar decisions are made across various parts of the organisation.	Increased potential benefits are realisable with little additional effort.
	Complexity	Complexity of the system's behaviour and thus the corresponding possible model.	Increased modelling effort and computational demands.
	Structuredness	Degree of structuredness of the decisions.	Increased applicability of the DSS.
	Decision Frequency	Frequency with which similar decisions are made.	Increased potential benefits of DSS.
Opportunity	User Capacity	Presence and availability of users with high system and model familiarity interested in developing DSS.	Decreased effort to generate a valuable DSS
	Developer Capacity	Presence and availability of developers with high system and model knowledge.	Decreased development time for DSS
	Existing Model	Existence of a recently used model.	Decreased development time and effort for DSS.
	Existing Deficit	Existence of a pressing problem situation with management attention to be solved.	Increased priority, and thus, reduced development time.
	Available Database	Availability of a comprehensive database suitable for modelling.	Decreased development time, particularly to the first benefits.

After the initial selection and development of a first application, the development of a multilayered DT of the GPN may commence. In some instances, it may be opportune to immediately establish connections to existing data sources or even establish a first instantiation of the data model and DB to leverage existing momentum. Alternatively, a systematic process is initiated to further develop the DT in alignment with the organisation's priorities, which is described in the next section.

4.5.2.2 Implementation Directions

In the second phase, several distinct development directions are available. Those are organised according to the layered structure shown in Figure 4-1 into (i) *data acquisition development*, (ii) *base model development*, and (iii) *application development*. As Figure

4-23 portrays, several directions exist within each layer. On the data acquisition layer, *data scope* denotes the extent of data across different similar parts of the organisation, data type describes the acquisition of distinct sets of data for new applications, data source specifies the sources used to obtain data, and data quality describes the improvement to the acquisition and preprocessing of data. On the base layer, *function development* denotes the development of new base-level functions, *function scope* denotes the extent to which functions are deployed across applications, and *database* describes the extension of the DB. Finally, on the application layer, *application scope* denotes the extension of existing DSS to new parts of the organisation, *application type*, the adaption to new usage forms introduced in 4.5.1.1, utilising the adaption options introduced in 4.3.3.1, *application methodology,* the methodological improvement of existing DSS and *application creation,* the development of new DSS for distinct PNC tasks.

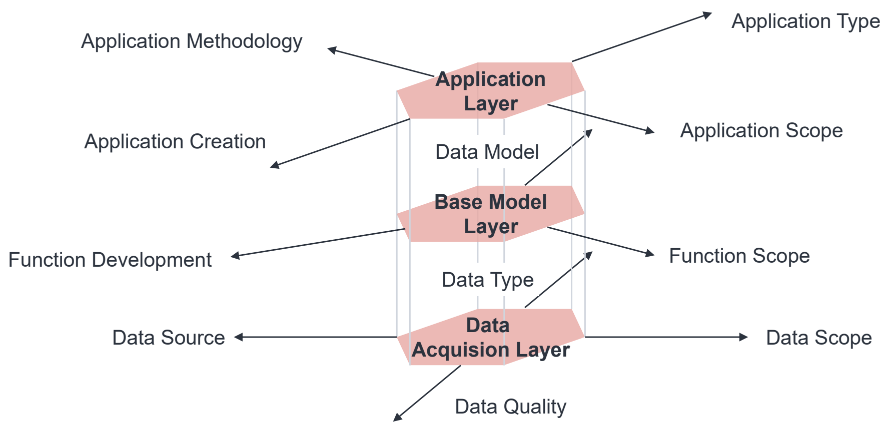

Figure 4-23: Fundamental Development Directions in the Expansion Phase

New developments can encompass multiple of these dimensions and can be modelled as a set of implementation items through which the costs and benefits may be evaluated. Each item belongs to a specific development direction. Furthermore, developments and their benefits can be predicated on prior developments on the same or a lower level. This may be captured in dependencies that one or multiple items may satisfy, as introduced in 4.4.3.2[57].

[57] For example, a DSS may require data on existing machines' capabilities. This dependency could be fulfilled by either a manual or an automated data acquisition process.

4.5.2.3 Development Portfolio Creation

Creating a development portfolio is a creative process, subject to the predisposition of the development team. Several ideation methods described in the literature can be applied to conceptualise new development options. A structured method is introduced in the following, based on the previously discussed development directions. Each development direction can be examined for potential progress to create a portfolio of development options. Different search questions are applied to determine opportunities, as each direction addresses distinct aspects. Table 4-20 provides an overview of the different directions and suitable search questions.

Table 4-20: Development Directions and Search Questions for Portfolio Development

Layer	Development Direction	Search Questions
Data Acquisition	Data Scope	Which domains/processes/partial systems can be connected with data acquisition to improve speed and quality?
	Data Type	Which additional data types can be retrieved from connected data sources?
	Data Source	Which additional data sources can be connected?
	Data Quality	Which preprocessing steps can be added to existing data acquisition strategies to improve the quality?
Base Model	Function Scope	To which other DSS could existing base model functions be extended?
	Database	Which additions need to be made to the DB?
	Function Development	Which additional base functions could support DSS?
Application	Application Scope	In which other domains/processes/partial systems can the DSS be applied?
	Application Type	In which other ways could the DSS or a variant of it be useful?
	Application Methodology	In what ways could the DSS be improved for current planning tasks?
	Application Creations	Which other planning tasks could be supported by adjacent DSS?

To adequately assess the benefits of first- and second-level developments, the already developed items and their dependent, unrealised benefits must be modelled[58].

4.5.2.4 Development Option Evaluation & Prioritisation

As discussed in 2.2.5.2, various criteria exist to evaluate DSS. The selection and prioritisation of criteria depend on the organisation's overarching culture, strategy, and objectives. The benefits introduced in 4.5.1.4 can be used to formulate specific criteria g. Their selection and prioritisation may vary by organisation. Pairwise comparison is applied to determine the relative importance and corresponding weight w_g of the criteria.

[58] The granularity of different development items is crucial for the efficiency of the proposed method. In principle, each new type of information can be regarded as an implementation item. A too granular interpretation makes the method overly complex and inefficient. Furthermore, it is never possible to anticipate all possible items and dependencies. Instead, a reasonable selection of items should be chosen, and dependencies within said selection should be uncovered.

Subsequently, the set of feasible development alternatives is defined as all possible combinations of items $\lambda \in \Lambda^{(IS)}$, where each fundamental dependency is satisfied. This set is then assessed and ranked using TOPSIS, where the weighed similarity to the best option, is used as a static utility $V_{\Lambda^{(IS)}}^{(STAT)}$ of a development option $\Lambda^{(IS)}$. To include a preference for quickly realised benefits, the realisation time for the different options can be assessed. This realisation time $\Delta\theta_{\Lambda^{(IS)}}^{(REAL)}$ can be approximated as $\Delta\theta_{\Lambda^{(IS)}}^{(REAL)} = \max_{\hat{r} \in \hat{R}^{(IR)}} \left(\frac{q_{\hat{r},\Lambda^{(IS)}}^{(ICD)}}{q_{\hat{r}}^{(AIC)}} \right)$, where $q_{\hat{r}}^{(AIC)}$ is the available yearly capacity of a relevant realisation resource type $\hat{r} \in \hat{R}^{(IR)}$ such as model developer, domain expert, etc. and $q_{\hat{r},\Lambda^{(IS)}}^{(ICD)}$ is the required capacity for the realisation of $\Lambda^{(IS)}$[59]. The dynamic utility of any option can then be determined as

$$V_{\Lambda^{(IS)}}^{(DYN)} = \frac{V_{\Lambda^{(IS)}}^{(STAT)}}{\left(\frac{\Delta\theta_{\Lambda^{(IS)}}^{(REAL)}}{\Delta\theta^{(REAL,REF)}} \right)^{\iota^{(DYN)}}}, \iota^{(DYN)} \in \mathbb{R}^{+} \qquad \text{Equation 4-17}$$

where $\iota^{(DYN)}$ denotes the immediacy preference of the organisation and $\Delta\theta^{(REAL,REF)}$ is the reference realisation time[60]. The option with the highest dynamic utility improvement rate $\dot{V}_{\Lambda^{(IS)}}^{(DYN)} = \frac{\partial V_{\Lambda^{(IS)}}^{(DYN)}}{\partial \theta}$ is chosen for development if $V_{\Lambda^{(IS)}}^{(STAT)} > 0$. Based on this combination, a roadmap can be designed as an ordered set of implementation strategies $\left(\Lambda_i^{(IS)}\right) \in \vec{\Lambda}^{(IS)}$, where:

$$\Lambda_{i_1}^{(IS)} = \left(\lambda_{i_2}\right)_{i_1} \subset \left(\lambda_{i_2}\right)_{i_1+1} = \Lambda_{i_1+1}^{(IS)} \; \forall \, \Lambda_{i_1}^{(IS)}, \Lambda_{i_1+1}^{(IS)} \in \vec{\Lambda}^{(IS)} \qquad \text{Equation 4-18}$$

and

$$V_{\Lambda_i^{(IS)}}^{(STAT)} \leq V_{\Lambda_{i+1}^{(IS)}}^{(STAT)} \; \forall \, \Lambda_i^{(IS)}, \Lambda_{i+1}^{(IS)} \in \vec{\Lambda}^{(IS)} \qquad \text{Equation 4-19}$$

Predecessors and successors of the initially chosen combination can be iteratively picked from the set of accepted predecessors or successors based on Equation 4-18.

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59 This assumes perfect divisibility and parallelisability of works.

60 $\Delta\theta^{(REAL,REF)}$ should be chosen, such that it is shorter than any possible realisation time.

Figure 4-24 shows this iterative roadmap creation process with forward and backward search.

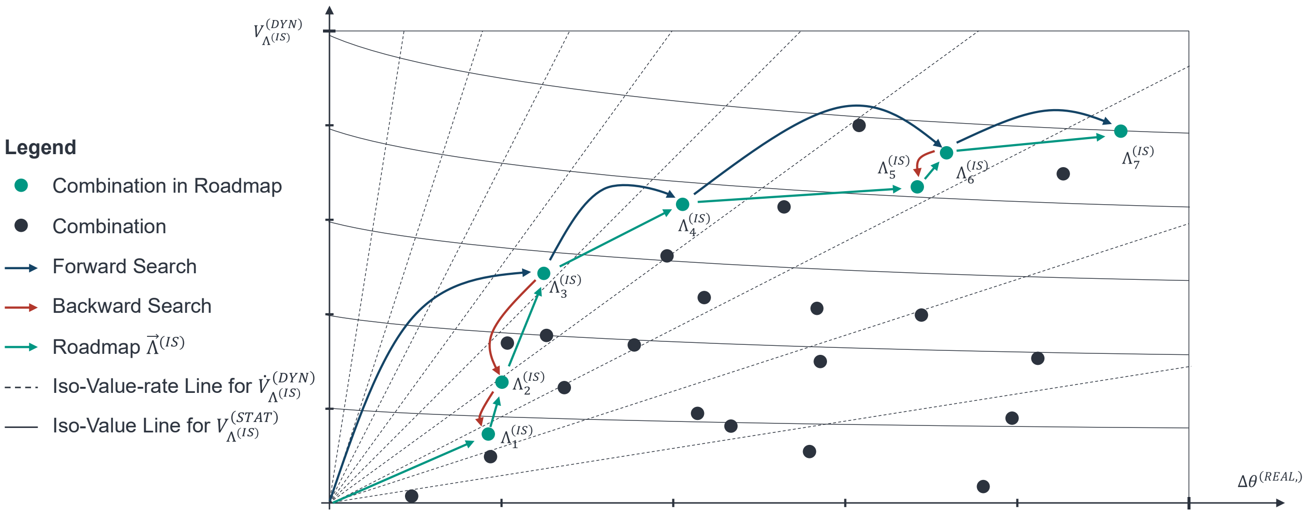

Figure 4-24: Iterative Roadmap Creation Process Based on Dynamic Utility Value Rate

Both the benefits of application-level items and the required implementation capacities for each item are difficult to assess, and the assessment may include significant uncertainty. As an implementation with limited complexity, the values can be assumed to follow a non-symmetric triangular distribution. Using MCS, the expected value $\mathbb{E}\left[\dot{V}_{\Lambda^{(IS)}}^{(DYN)}\right]$ and the standard deviation $\varsigma\left[\dot{V}_{\Lambda^{(IS)}}^{(DYN)}\right]$ can be calculated. Subsequently an optimistic utility rate $\dot{V}_{\Lambda^{(IS)}}^{(DYN,OPT)} = \mathbb{E}\left[\dot{V}_{\Lambda^{(IS)}}^{(DYN)}\right]$ and a pessimistic utility rate $\dot{V}_{\Lambda^{(IS)}}^{(DYN,PES)} = \mathbb{E}\left[\dot{V}_{\Lambda^{(IS)}}^{(DYN)}\right] - \varsigma\left[\dot{V}_{\Lambda^{(IS)}}^{(DYN)}\right]$ are determined. Then, the preferred solution can be chosen from a Pareto curve of both, depending on the risk preference of the decision-makers. Assuming a consistent risk preference of the organisation, a set of Pareto-efficient implementation roadmaps can be generated.

This methodology ensures that complementary developments, in terms of resource demands and short-term benefits, are preferred while also contributing to the long-term benefits of the DT. A more detailed depiction of this methodology, including specifics of TOPSIS, is provided in Appendix A5.3.

5 Validation

The framework developed in Chapter 4 is tested in an industrial use case of an automotive supplier with a large GPN and a wide variety of products. Section 5.1 introduces the basic characteristics of the company, its GPN, and typical production system, the existing planning processes and the data landscape. Subsequently, Sections 5.2, 5.3, 5.4, and 5.5 discuss the application of the framework introduced in Chapter 4, in order.

5.1 Introduction of the Industrial Use Case

This first section provides a broad overview of the validation use case to establish a context for instantiating the framework developed in the previous chapter. Thus, the focused company, production system, processes and organisational setting, and data landscape are presented.

5.1.1 Company Characteristics

The focal company is a large manufacturer with several business segments, the largest of which is the automotive & mobility segment, which is the focus of this case study. The company primarily operates as a tier-one supplier within the automotive segment, selling components to original equipment manufacturers (OEMs). These products are sold under a master order, governing the product specifications and volume outlines, typically with included flexibility. Within the framework agreement, customers specify volumes with individual orders. The company differentiates itself through a broad spectrum of factors, following a classic producer strategy (Thomas, 2013, pp. 130–131).

5.1.2 Production System Characteristics

Within the segment, the company operates over 100 production sites globally, which are organised into different product-oriented divisions. Each division has a product portfolio, with product groups produced across a network of sites, internally referred to as the International Production Network (IPN). Any site can be a part of multiple IPNs. The company has a relatively high level of vertical integration, as it fabricates many of the components for its products internally before assembly. The IPNs are typically organised in a hub-and-spoke-like structure, with fabrication done only at a few locations, while usually all sites of an IPN assemble parts. However, some of the fabrication is also performed in a local-for-local fashion. Some IPNs also act as internal suppliers for other IPNs. The products are typically high-volume, high-variance. Most products can be transported in standard transport units, with moderately high value density. Assembly is performed as an automated or semi-automated flow production. Fabrication is usually decoupled from assembly and organised as a workshop or flow production.

5.1.3 Process Landscape & Organisational Setting

The PNC decisions of interest in this case study are focused on capacity and capability allocation. For these, the company has designed a rolling yearly planning process, which involves several operations-related functions of the company (Stoi, & Asenkerschbaumer et al., 2015). Within this process, each IPN must allocate planned production volumes through a process called planned volume allocation (PVA). This plan determines necessary investments in releases, additional line capabilities, line additions and shutdowns, and personnel and material demand. Additionally, volumes for internal suppliers and their allocation needs to be determined. For this process, each IPN is given two weeks. Afterwards, investments are planned further in more detail, considering space and personnel capacity across multiple IPNs in a process called Long Term Planning and Site Strategy Manufacturing (LTP-M). IPN planners, site production management, logistics planning, controlling, and divisional production planners are involved in this process. The process considers a seven-year time horizon with half-year planning periods. Several unscheduled planning variants are performed outside the above-described routine planning cycle. When drastic changes occur in the order program or strategic setting, order allocations and site strategy can be reevaluated throughout the year. Investment decisions are also typically prepared across a more extended timeframe and including several scenarios.

5.1.4 Data Landscape

The data for the planning processes originates from several different sources. Production orders are generated by the sales department, which organises their multi-period order data in their CRM system, including preliminary allocation of orders to sites while not considering capacities. Product variant features and matching production capabilities are available in very heterogeneous forms. While product features are stored in the PLM system, they are not easily translated into necessary production capabilities. Production resources are defined in the ERP system, including planned process times. Resource capabilities are not stored consistently across IPNs. Actual processing times and resource availability are reported through the MES system. The company has recently specified a reference model for its production DM called Core Information Model Manufacturing (CIMM), which is used as a basis for the company-specific DM.

5.2 Decision Support System Design

In the following, the methodology for DSS design developed in 4.2 is applied in two subcases of the previously introduced industrial use case. 5.2.1 critically examines the design of a previously developed solution for the PVA process called Automated Planned Volume Allocation (APVA), and 5.2.2 develops a new DSS for the subsequent LTP-M process called Long Term Planning Assistant (LTPA). Both solutions have been implemented as part of the same digital twin framework within the industrial use case.

5.2.1 Automated Planned Volume Allocation

This subsection critically examines the APVA tool, which was developed to support the PVA process. It is described in more detail by Brützel et al. (2021), Brützel et al. (2022), and Brützel et al. (2025). The DSS aims to support IPN planners in optimally allocating production volumes and the necessary resource adjustments. To assess the design of the APVA tool, the DSS design phases introduced in 4.2.3 are carried out for the model, and the resulting design recommendations are compared with those of the implemented tool. This detailed analysis of the APVA design is shown in Appendix A6.

5.2.2 Long-Term Planning Assistant

This subsection describes the design of the LTPA tool, which is intended to support site capacity planning and strategic decision-making for online allocations. The tool is the result of the master's theses A_Bauer (2023), A_Steinkühler (2023), and A_Bolender (2024), supervised by the author. This section outlines the DSS design. A more detailed description is provided in Appendix A7 and Benfer et al. (2024).

5.2.2.1 Decision Type Analysis

The first phase of the LTPA development process consists of three steps: (i) determination of the time horizon, (ii) selection of major system elements, and (iii) deduction of desired AC. Figure 5-1 depicts this process, which is further detailed in Appendix A7.1.

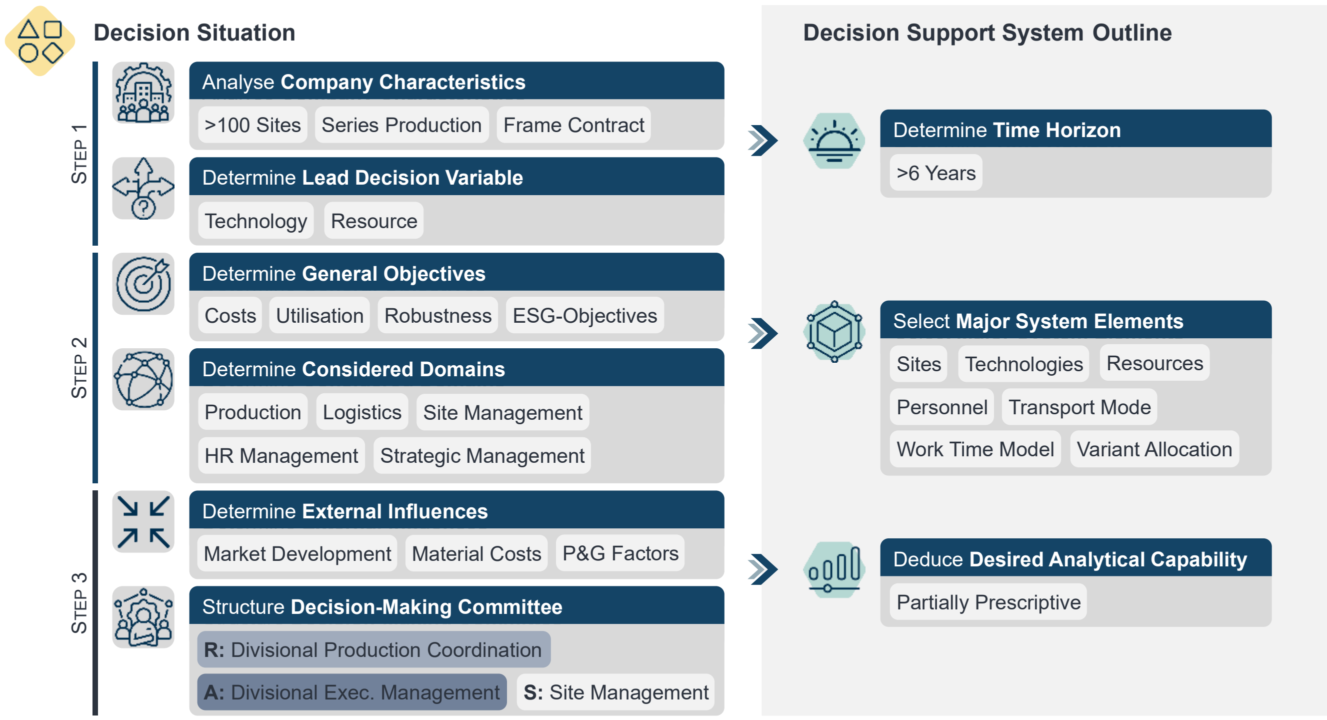

Figure 5-1: Overview of the Decision Type Analysis for LTPA

5.2.2.1.1 Determination of the Time Horizon

The first step in the decision type analysis is to determine company characteristics, as described in 5.1.1. Next, the lead decision variable needs to be defined. The decision process that the DSS is supposed to support focuses on configuring production resources such as machines and assembly lines. Decisions on new sites are assumed to be fixed, but expansions and consolidations may be considered. Under normal circumstances, the process does not consider changes in production technology, but the DSS may be used that way under specific circumstances. Based on typical set-up times for production resources of 12-24 months, the time horizon should be at least 3 years. The existing 8-year time horizon aligns reasonably well with the typical setup times of new technologies, which range from 0.5 to 3 years.

5.2.2.1.2 Selection of Major System Elements

Step 2 begins with determining objectives. The decision focuses on partial costs for the decision as well as the utilisation of production facilities and personnel capacity. Secondary objectives are quality and flexibility. The primary domain is production, encompassing multiple business units. The process also involves procurement, logistics, and sales as a secondary consideration. Capability and capacity decisions must be aligned with the availability of materials. Logistic costs may influence operating costs, and sales is responsible for future order volumes in different markets. The major system elements to be modelled are sites, lines, buildings, and personnel.

5.2.2.1.3 Deduction of Desired Analytical Capability

Step three of the decision type analysis commences with the examination of external influences on the decision. For the planning of capacities across sites, market development, factor costs, political, and social factors are found to be relevant. The DMC is primarily composed of the central manufacturing department and site management, though the IPN management is also involved. Considering the different influences on the desired AC according to the evaluation model introduced in 4.2.3.1.3, a partially prescriptive DSS is found to be favourable.

5.2.2.2 Method Composition

Next, the DSS needs to be composed as shown in Figure 5-2.

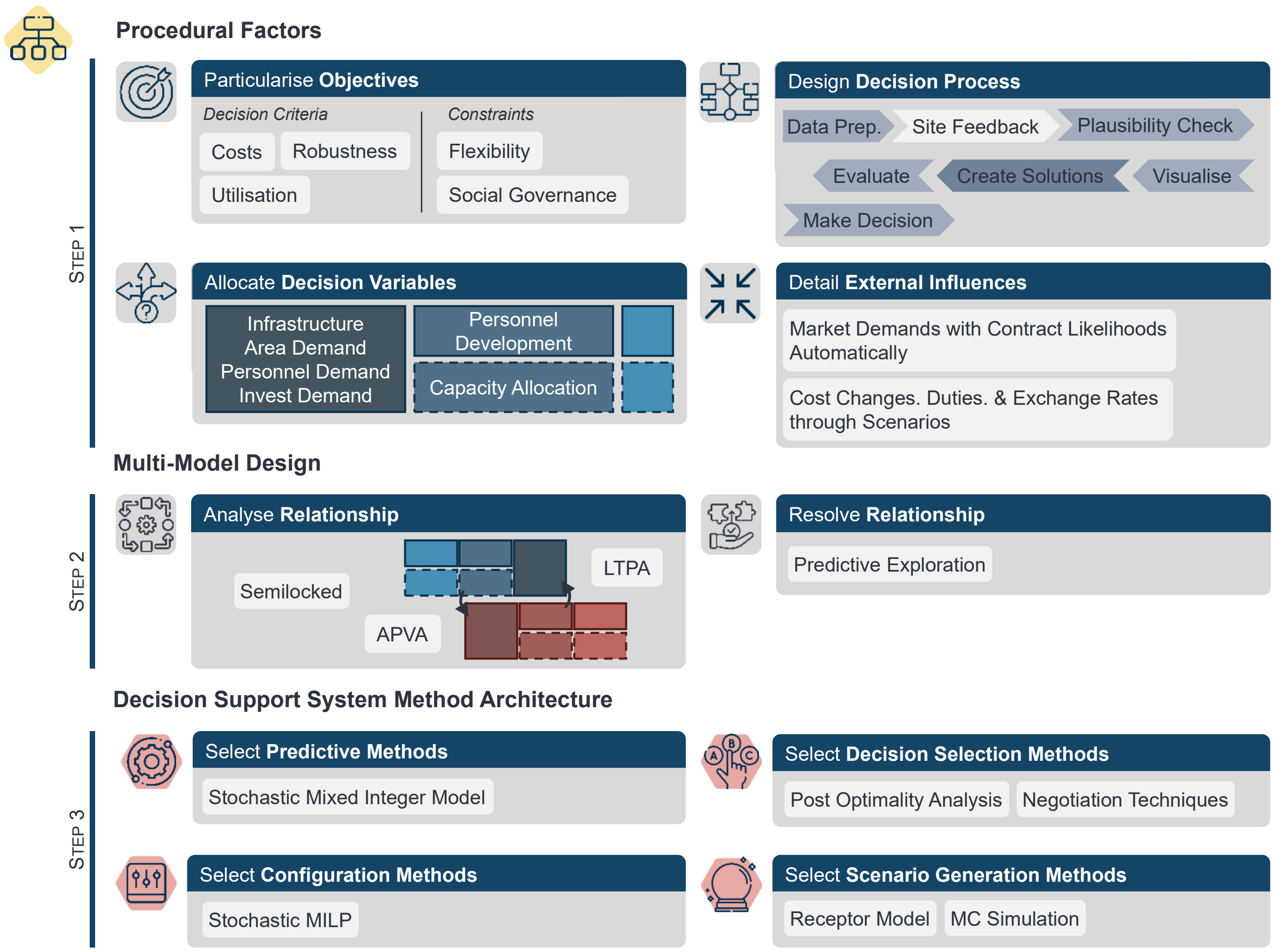

Figure 5-2: Overview of LTPA Method Composition

The process comprises three steps, (i) procedural factor determination, (ii) multi-model design with APVA, and (iii) DSS method architecture. Each of those steps is further discussed in the subsequent paragraphs. A more detailed account of the considerations involved is given in Appendix A7.2.

5.2.2.2.1 Procedural Factor Determination

First, procedural factors, such as objectives, decision variables, the decision process, and external influences, are further specified based on the results of Phase 1.

The particularisation of objectives involves specifying which aspects of the objectives are considered and how, as well as whether they should be regarded as a condition that must be met to satisfaction or an objective that needs to be improved as much as possible. In this case, operational costs and equipment investments are considered as objectives. Infrastructure costs, which are not directly affected by LTPA decisions, are not taken into account. instead, the utilisation of infrastructure in terms of productive area quota is used. The robustness of solutions, especially in the face of changes in market demand, is regarded as a key objective. In particular, the likelihood of major deficiencies in fulfilling market demand due to area, personnel, or investment restrictions should be minimised. Finally, worker protection is considered a boundary condition, and greenhouse gas emissions associated with material, production, and logistics are integrated into the costs.

Decision variable allocation attributes the decisions made in LTPA to the different sets introduced in 4.2.2.1.2. In particular, infrastructure development and budgets, as well as demand for area, personnel, and investments, are considered fixed. Decisions on personnel development are subject to the decision and can be made relatively easily with prescriptive calculation. The allocation of area, personnel, and investment to IPN requires managerial prioritisation and is thus part of the predictive subject set.

Decision process design involves specifying the steps of the decision process and the responsible stakeholders. The decision process largely follows the LTP-M process.

External influence characterisation involves detailing the effect of external influences on decisions and how they should be incorporated. Changes in market demand are found to be the primary external factor driving capacity demand. As they involve the interaction of several factors and lie outside the domain the decision process is primarily concerned with, they are included as discretised predicted probability densities. Other influences, like material cost changes, duties, and changes in currency exchange rates[61], are considered in manually defined scenarios.

5.2.2.2.2 Multi-Modell Design & Interaction with APVA

The next step is considering the relationship between APVA and LTPA. The relationship is described using the decision variable sets. The result is a semi-locked relationship between APVA and LTPA, formally $m^{(APVA)} \rightharpoonup m^{(LTPA)}$, as LTPA depends on the prescriptive subject set of APVA and APVA depends on the predictive subject set of LTPA. In less abstract terms, LTPA requires the capacity demand figures from APVA, whereas APVA requires the available capacity from LTPA.

To solve this semi-locked relationship, the predictive exploration strategy is chosen, as it aligns closely with the desired decision process, and a combination or subsumption of LTPA with APVA would be computationally too expensive. Prescriptive exploration is considered possible in theory but not pursued further to limit complexity. In practice, LTPA determines the capacity allocation to each IPN, and APVA calculates the prescriptive LTPA results based on this allocation. This combination also allows LTPA to outsource a significant part of the operating cost calculation to APVA.

5.2.2.2.3 DSS Method Architecture

The third step of phase two involves selecting methods for the DSS. For the capacity calculations, a stochastic linear model is chosen. It effectively captures personnel development and investment budgets, making it suitable for exact optimisation. However, it can only capture area capacity with very limited accuracy. The decision-making process utilises post-optimality analysis in APVA decisions and negotiation techniques in capacity allocation. For the prescriptive solution of both APVA and personnel planning, stochastic MILP is used due to its applicability to the prescriptive models and the number of decisions to be made. A receptor model and MC simulation are applied for the production demand scenarios. LTPA does not use any meta-heuristics.

[61] Currency exchange rate changes are bookmarked for a probability-density-based representation, once relevant data is available and included in the model.

5.2.2.3 Model Detailing

Finally, decisions on model detailing are required, as shown in Figure 5-3. This process is detailed in Appendix A7.3. It involves specifying requirements and restrictions, as well as further detailing the DSS, with a focus on the predictive and prescriptive models at its core. Additionally, the data demand from LTPA is gathered. These demands are not depicted in Figure 5-3 to save space. They are discussed in detail in Appendix A7.3.

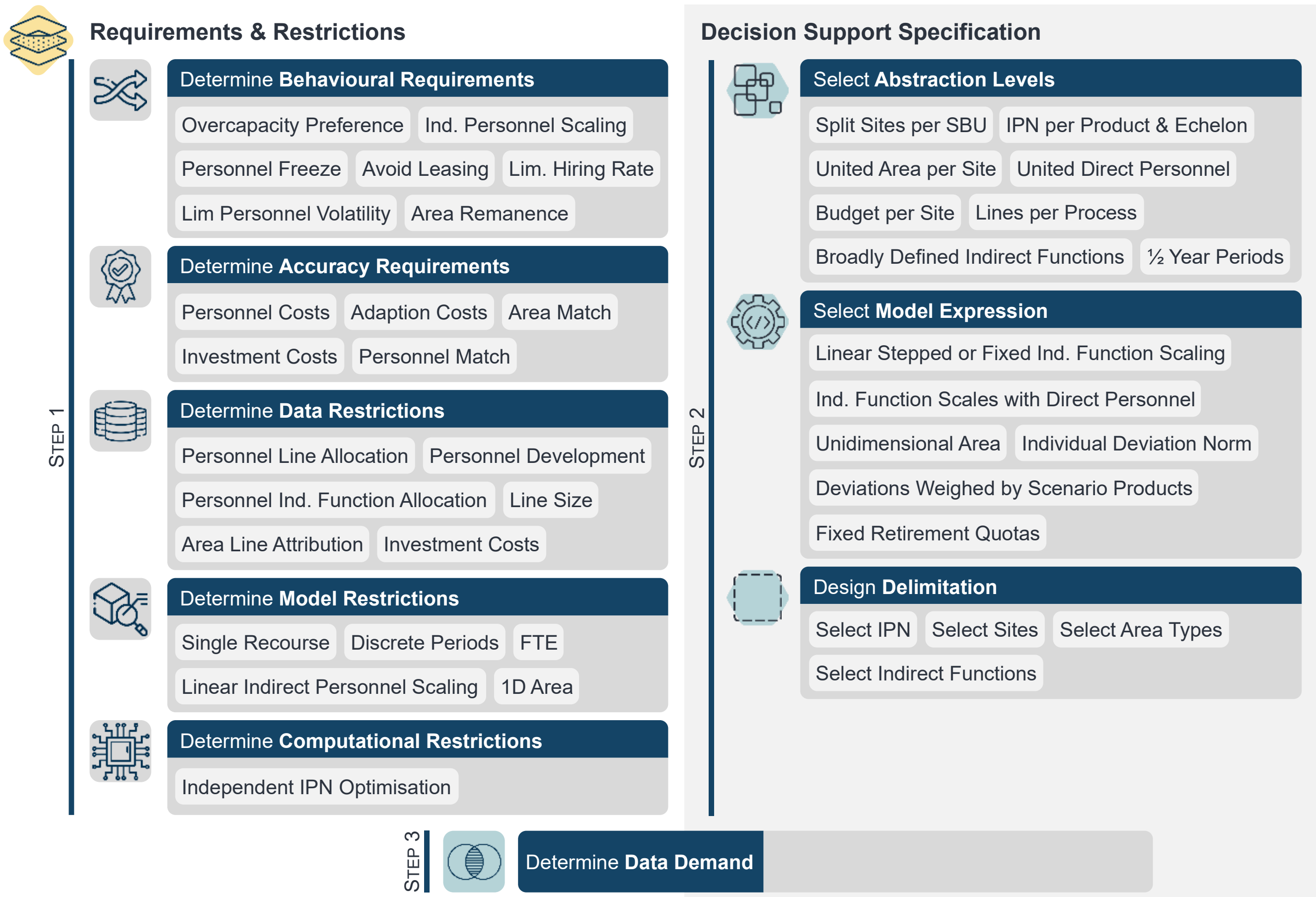

Figure 5-3: Overview of Method Detailing for LTPA

5.2.2.3.1 Requirements & Restrictions

In the following, the requirements for the behavioural representation of the model and its accuracy, as well as the restrictions due to data availability, modelling method characteristics and computational restrictions are described. Important requirements for the model include the remanence of the occupied area after line consolidation to account for reconstruction time, and the rolling freezing of personnel planning, i.e., decisions made in the next year must be the same for all scenarios. In terms of accuracy, the costs of decisions should be within 10% accuracy for personnel and 20% for other decisions. To avoid planning issues, the demand match for personnel and area should be within 10% and 5% accuracy, respectively[62]. The available data only offers area per production system, aggregating multiple lines. Personnel development figures are only available for the entire site, distinguishing between direct and indirect personnel. The linear model only allows for a flattened consideration of the area match; shape-specific aspects cannot be taken into account. Finally, computational resources require the separate optimisation of IPNs to control problem size.

5.2.2.3.2 DSS Specification

Based on the previously determined requirements and restrictions, the abstraction level, model expression and delimitations are specified, and data demands are determined. Abstraction involves limiting area considerations to sites instead of buildings, aggregating personnel to direct and indirect staff per site, regardless of training levels, age distribution, and wage levels. The model expression includes several choices. For example, personnel over- and undercapacity are implemented as soft constraints to ensure solvability and enable a solution through APVA. According to the model restrictions, area is considered a scalar, regardless of shape, assuming a constant space efficiency of lines. The scaling factor between direct and indirect personnel is assumed to be constant. Furthermore, personnel demand is assumed to scale linearly with line utilisation. Only a few delimitations have to be made. Area occupied by and personnel of other business units are assumed to be fixed and not modelled in detail. The set of included sites and IPNs can be chosen. Finally, data demands are determined, including detailed site and production system-specific area data, nominal personnel requirements for lines, and personnel development figures such as planned retirements.

5.2.2.4 Resulting LTPA DSS

The resulting LTPA DSS, depicted in Figure 5-4, aids the divisional manufacturing coordination in capacity planning. It aggregates the results of APVA-based IPN plans for allocating product variants and changes to production equipment. Using capacity factors, the capacity demands for each IPN at each site for personnel, area, and investments are determined and compared with the available site capacity. The available personnel capacity is determined prescriptively within a set of constraints. Subsequently,

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[62] More precise stipulations are provided in Appendix A7.3.

capacity deviations can be detected. Using capacity-restrained APVA optimisation strategies to resolve these deviations can be developed and evaluated using NPV.

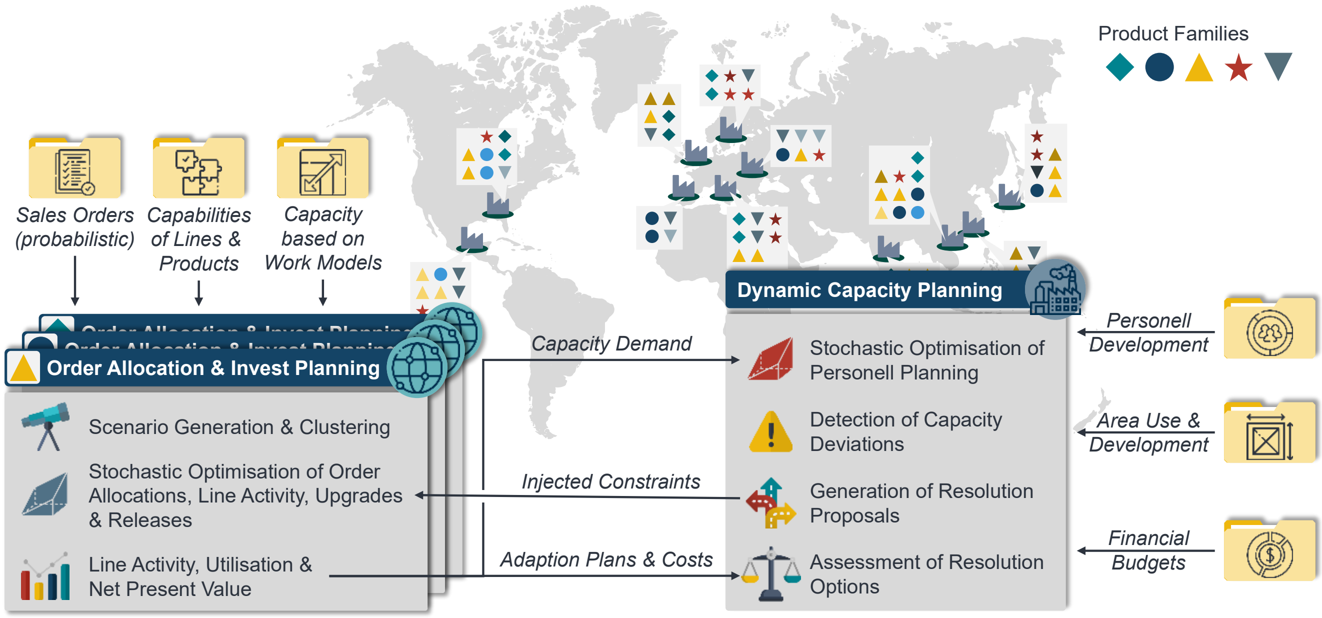

Figure 5-4: Integrated Two-Model Concept for Site Capacity Planning

To address the uncertainty regarding the market and market development, IPN-specific scenarios are utilised. I.e. every IPN p provides a set of scenarios $\omega \in \Omega_p^{(IPN)}$ with corresponding weights w_ω capacity demands. These scenarios are translated into site-specific sets of scenarios used in the personnel planning model, against which the available capacity is tested. A detailed description of LTPA is provided in Appendix A8.

5.3 Digital Twin Architecture

Building on the previously developed APVA, a digital twin architecture is created. It considers the industrial partner's specific requirements using the approach developed in 4.3. This architecture consists of a DM and a DB adapted for the requirements of APVA and LTPA introduced in 5.3.1, a versioning schema implemented for LTPA and APVA described in 5.3.2, calibration methods for APVA discussed in 5.3.3, a model interaction design structuring the relation between LTPA and APVA, portrayed in 5.3.4, and a model generation algorithm for LTPA shown in 5.3.5.

5.3.1 Common Data Model and Database

To support the operation of both APVA and LTPA, a DM was developed by A_Orhan (2022), A_Bramey (2023), and A_Feldinger (2023). A multistep process is applied to accommodate both the applications' specific requirements and the company's broader standards. Initially, the specific requirements of APVA were compared with the general DM developed in 4.3.1.2. Subsequently, the model aligns with the company's general DM CIMM, focusing on structure and terminology. The result is the DM v2 for the PNC tasks of the company. A relational DB is selected for implementation based on further analysis of the DM and the application requirements. Next, the elements necessary for APVA are implemented in DB v1. Subsequently, additional LTPA-specific elements and properties and elements necessary for the versioning discussed in 5.3.2, are added to arrive at the DM v3 and DB v2. The applied process is depicted in Figure 5-5.

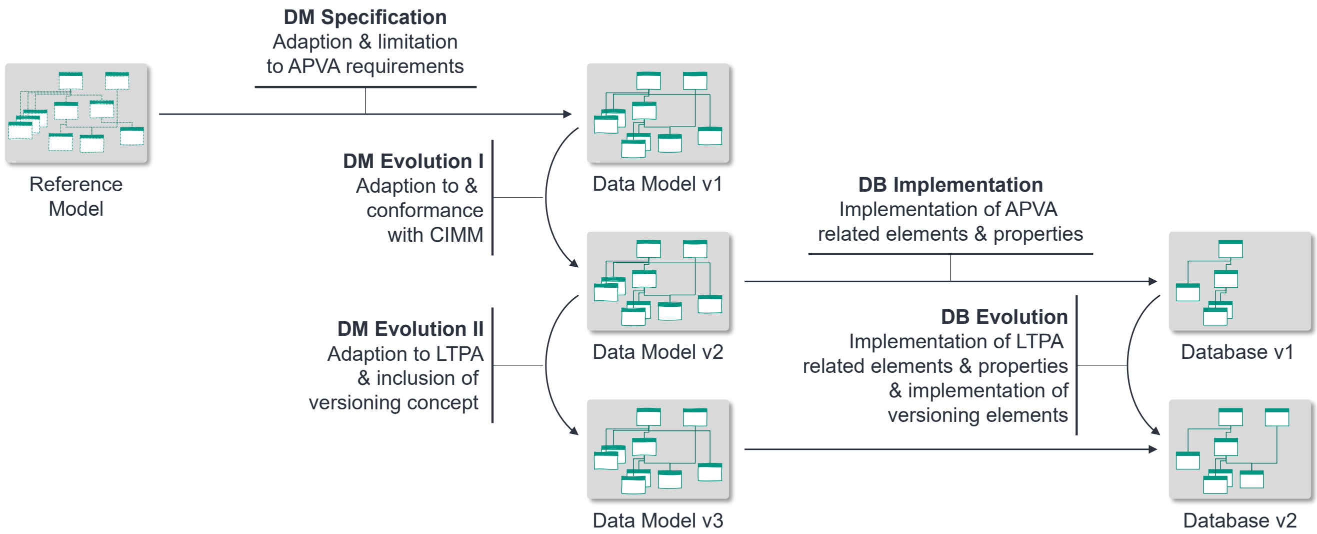

Figure 5-5: Procedure to Create the Data Model and Database for the Validation Case

5.3.2 Versioning

A central component of the DB concept described in 4.3.1 is the versioning of information, specifically planning data. The implementation realised in the validation case uses a complex of several elements in the DB to ensure a set of requirements is fulfilled. The implementation results from the master's theses A_Feldinger (2023) and A_Bolender (2024) supervised by the author.

The DB implemented in the validation case is utilised by multiple groups of users of APVA and LTPA. Both DSSs are stochastic and interact with each other. Thus, the DB must allow DSS to both read and write data. The data needs to be traceable to its origin and differentiated access management based on information type and content is necessary, as, for example, different IPN planners are not allowed to access each other's information. A specification of stochastic plans and their likelihood of occurrence in the

DB must be possible. As both APVA and LTPA can be performed with different parameters, and the set of parameters is DSS-dependent, a flexible approach needs to be devised to store these parameters.

Figure 5-6 shows the core elements of the versioning implementation in the DB. The centre of the versioning in the DB is the *version*. All elements in the DB are connected to one specific version, ensuring traceability. As specified in 4.3.1.5, versions are organised in *scenario spaces* that belong to a specific user and data source. Within scenario spaces, information about the current state and weight, i.e. likelihood of a version, is organised. The *data source* represents a general type of information source, e.g., APVA or LTPA. It specifies which information the source demands from and provides to the DB in a definition schema. Data demands can be fulfilled by *version uses*, encoding that a version uses data from another version. The data source also defines a format for model parameters, which are the set of meta-parameters of the model. These *model parameters* are stored as JavaScript Object Notation (JSON) files.

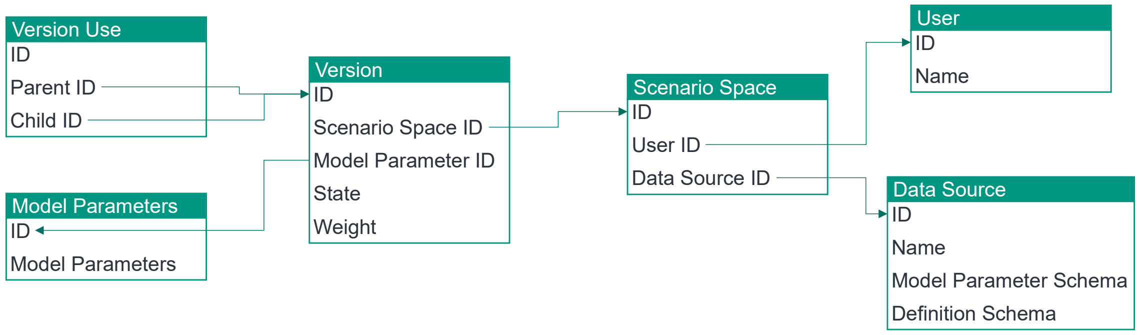

Figure 5-6: Core Elements in Versioning Implementation

5.3.3 Calibration

Utilising the priority assessment introduced in 4.3.2.1, the data demands of APVA are analysed. Based on this, information on overall equipment efficiency per line, cycle times of products and feature costs are found to have the highest calibration priority. Subsequently, calibration services for these parameters are conceptualised as shown in Table 5-1. A more detailed analysis of the calibration services is provided in Appendix A9.1. Calibration services for LTPA could be designed in the same manner.

A more detailed analysis of the calibration services is provided in Appendix A9.1. Calibration services for LTPA could be designed in the same manner.Table 5-1: Conceptualised Calibration Services for APVA

Table 5-1: Conceptualised Calibration Services for APVA

Calibration Service	Data Demands Served	Data Source	Type
CS01	line_OEE	MES	ex-ante
CS02	cycle_time	MES	rule-based
CS03	feature_costs	ERP	on demand
CS04	fix_costs per line	MES	frequency

5.3.4 Model Interactions

As described in 5.2.2.3, APVA and LTPA concern related decisions. Specifically, LTPA decisions embed APVA decisions. Therefore, a request-response interaction is implemented, allowing LTPA to specify an APVA run with additional injected constraints. Details of the design process and implementation are provided in Appendix A7.2. In the future, several additional interactions may be implemented, such as a publish-subscribe interaction that updates LTPA whenever new APVA results become available, and a capacity-based interaction to determine optimal resolution strategies for capacity deviations. Additional implemented and planned interactions in the model complex of the organisation may be found in Benfer et al. (2023).

5.3.5 Model Generation

Overall, APVA is included in a well-specified process, and the model is entirely parametrised, so automatic model generation is possible. However, some decisions concerning specific model design can be determined through parameterisation. Those are shown in Table 5-2[63].

Table 5-2: Adaption Options in APVA Model Generation

Type	Element/Feature	Options
Abstraction	Orders	By customers, by feature demands, by releases
	Line Features	By product feature demands, by investment necessity,
Functional Representation	Scenarios	No recourse, partial recourse, full recourse
	Scenario Weights	Proportional, equal
	Inbound Flexibility	Not included, included
	Outbound Flexibility	Not included, included
Delimitation	IPN	Select one

Generating an LTPA model primarily involves questions of delimitation and functional representation. Specifically, users may decide on the set of relevant sites and products, as well as the integration of indirect functions, which may require several replacement

[63] These decisions were not designed or implemented by the author of this work but were merely formalised according to the theoretical foundations described in 4.3.3.

elements. The functional expression of indirect functions may also vary depending on the available data. This relatively limited set of adaption options may be expanded upon in the future. An overview of these aspects is given in Table 5-3.

Table 5-3: Adaption Options in LTPA Model Generation

Type	Element/Feature	Options
Functional Representation	Indirect Function Scaling	Linear stepped, fixed
Delimitation	IPNs	Select set
	Sites	Select set
	Indirect Functions	Not included, included

5.4 Data Acquisition

As indicated in 5.1.3, the relevant processes and data sources were established prior to the development of APVA and LTPA. Thus, this section only covers the most relevant additions according to the procedure defined in 4.4. 5.4.1 discusses the analysis of relevant data sources, followed by specific data acquisition strategies developed in 5.4.2, and preliminary assessed in 5.4.3.

5.4.1 Data Sources

The data demands established in the DSS design may be drawn from several data sources. Table 5-4 provides an overview of the relevant data sources and acquisition strategies for APVA.

Table 5-4: Relevant Existing Data Sources and Acquisition Strategies

Data Demand	Demand Description	Existing Acquisition Strategy	Data Source
Order Information	Order ID, product variant, customer, volumes, likelihood,	File-based Transfer	Sales-Planning System
Line Information	Line ID, site	Manual	File-based Information
Line Capabilities	Line ID, site, product	Manual	File-based Information
Customer Releases	Releases for sites and lines	File-based Transfer, Automatic Transformation	File-based Information
Line Capacity	OEE, yearly average and maximum working hours	File-based Transfer	File-based Information
Allocation Boundary Conditions	Fixed allocation of orders and production volumes to sites	Manual	File-based Information
Production Costs	Fixed and variable costs of production per line, costs of over- and underutilisation	File-based Transfer, Manual Transformation	ERP System
Release Costs	Costs of customer releases	Manual	File-based Information
Logistic Costs	Inbound and outbound logistics costs for products and connections, material costs	File-based Transfer, Automatic Transformation	Logistics Planning System
Process Times	Planned process time per line and product variant	File-based Transfer, Manual Transformation	MES

As PVA and LTP-M are defined processes, a set of sources is already defined. However, only a subset of data is stored in IS, including sales data, cost figures, product variant designations, demographic data, and information on existing resources. Other data, such as line capabilities, product variant features, and available area, are stored as files. Overall, the data acquisition is highly manual.

5.4.2 Data Acquisition

The data acquisition strategies (AS) for many of the data demands already exist before the application of the framework presented here. Table 5-5 shows an overview of the developed candidate data acquisition strategies structured according to 4.4.2. Data acquisition strategies for LTPA concerning area capacity use and employees are created for this work. Area capacity and usage are specified in the company's ERP system. As the required frequency is low, a manual export is chosen for the first version. Areas are allocated to lines and indirect areas based on usage classes. Preprocessing to remove duplicates and ensure data quality is necessary. Employee capacity data are provided through the Human Resources (HR) department via an Excel export. Only minimal preprocessing is needed. The excerpt of data acquisition processes shown here is expanded in Appendix A10.1.

Table 5-5: Analysis of Created and Candidate Data Acquisition Strategies (Excerpt)

Acquisition Strategy	Data Demands Served	Data Collection Methods	Synchronisation	Preprocessing Methods
AS01	Material Prices	Structuring from an xlsx file	on demand	Imputation, Schema Matching, Dimensionality Reduction
AS02	Material Prices	Interface with ERP	on demand	Imputation, Schema Matching, Dimensionality Reduction
AS03	Order Volumes and Likelihoods	Interface with sales IS	on demand	Imputation, Advanced Transformation
AS04	Machine Utilisations	Interface with Production Data Lake	frequency based	Imputation, Noise Reduction, Advanced Transformation
AS05	Technical Capacity	Interface with Production Data Lake	on demand	Imputation, Advanced Transformation
AS06	Variable Cost	Interface with ERP	frequency based	Imputation, Advanced Transformation
AS07	Fix Cost	Interface with ERP	frequency based	Imputation, Advanced Transformation

5.4.3 Data Acquisition Assessment

The candidate data acquisition strategies (AS) are assessed, corresponding to the procedure outlined in 4.4.3. Where applicable, multiple different alternatives are compared.

As evaluation criteria, (i) the setup time, (ii) the capital value, (iii) the achievable accuracy, (iv) the timeliness, (v) the consistency, (vi) the completeness, and (vii) the resulting acquisition time are chosen. Set-up time and capital value are determined based on the estimated effort and availability of required stakeholders. The capital values only include costs incurred or evaded directly by the acquisition strategy; effects based on dependent benefits are excluded. The criteria iii-v are evaluated on a scale of 0 to 1. An excerpt of the comparison is portrayed in Table 5-6. A comprehensive overview is given in Appendix A10.2.

Table 5-6: Data Acquisition Strategy Assessment (Excerpt)

Data Acquisition Strategy (AS)	Set-Up Time Estimate [m]	Capital Value [€]	Accuracy	Timeliness	Consistency	Completeness	Acquisition Time [d]
AS01	1	-14,000	0.8	0.7	0.7	0.8	2±1
AS02	2	-36,000	0.9	0.9	0.9	0.9	
AS03	2	-25,000	1	1	1	1	
AS04	1	-24,000	1	1	1	1	
AS05	1	-24,000	1	1	1	1	
AS06	2	-18,000	1	1	1	1	
AS07	2	-18,000	1	1	1	1	

5.5 Organisational Integration

This section illustrates the integration of the DT into the validation case organisation using the structure described in 4.5. First, 5.5.1 illustrates relevant additional usage forms for APVA and LTPA based on the framework outlined in 4.5.1. Subsequently, 5.5.2 documents the systematic implementation procedure used in the validation case.

5.5.1 Additional Usage Forms

While there are several alternative application types for APVA and LTPA, two prominent ones are discussed here, with a detailed analysis of all potential application types and Appendix A11.1.

Whereas APVA is designed primarily as a scheduled planning DSS with deterministic realisation, other application types are conceivable. A promising approach is the use as an exploratory teaching tool to investigate broader possibilities and scenarios using a user-specified DoE method. This solution is pertinent, as the DSS is, in principle, applicable to a broad scope of settings, the system uncertainty is significant, and the users' system expertise is relatively high. To realise, the usability of the DSS regarding the specification of such scenarios, interpretability of the result and robustness with regard to insolvabilities needs to be increased. This application could further enhance user system knowledge and reduce reaction times for unforeseen disruptions. It could also lead to considering new system adaptations, which may be overlooked in scheduled planning.

LTPA could be adapted for educational use, allowing users to better understand the behaviour of the multi-product GPN. The DSS already has an approachable AC and allows for dynamic interactions. The system knowledge of potential users is limited due to the heterogeneity of IPNs. Additional interactions, in the sense of parameters that are open for manipulation, need to be established to create this application. Users need to be better supported in their interaction with the system, for example, through the automatic visualisation of results. This application could serve a broad group of users to better understand the behaviour of different IPNs. Decision-makers could increase their system knowledge to make more informed and intuitive decisions.

5.5.2 Implementation Procedure

In the validation case, APVA is used as the initial DSS upon which the DT is built. In the following, the focus is on the expansion phase. A discussion of phases one to three may be found in Appendix A11.2. To determine the future development directions for the solution implemented in the validation case, a comprehensive portfolio analysis is conducted using the methodology introduced in 4.5.2. This analysis involves exploring development directions, deducing a consistent development portfolio, and evaluating and prioritising.

5.5.2.1 Development Portfolio

Based on the procedure established in 4.5.2.3, a portfolio of available implementation items (II) is generated. Then, a selection of these items is created based on the maturity of their conceptualisation, as shown in Table 5-7, and used for further analysis. Based on input from the organisation, the relevant benefit types and scales are determined, and weights for the benefit types are deduced using pairwise analysis. For each application-level and base model item, categorical benefits are determined based on user and development team estimations. For both existing and new application-level items, enhancing dependencies are determined. Furthermore, items that fulfil the dependencies are identified at both the base model and data acquisition levels. Using the categorical dependencies, the feasible combinations are determined by eliminating all sets with unfulfilled categorical dependencies. The entire process is discussed in detail in Appendix A11.3.

Table 5-7: Selected Implementation Items for Analysis

Layer	Development Direction	Identified Items	
Data Acquisition	Data Scope	II15	Material Price Import Form (AS01)
		II16	Automatic Material Price Import from ERP System (AS02)
		II17	Sales Forecast Import from Sales IS (AS03)
		II19	Machine Utilisations from Production Data Lake (AS04)
		II20	Technical Capacity Import from Production Data Lake (AS05)
		II21	Variable Cost Import from ERP System (AS06)
		II22	Fix Cost Import from ERP System (AS07)
		II23	Automatic Logistic Cost Import from Logistics Planning System (AS08)
		II24	Station Capability Import Form (AS09)
		II25	Product Feature Import from BOM (AS10)
		II26	Automatic Station Capability Import (AS11)
		II28	Site Area Import Form (AS12)
		II29	Automatic Site Area Import (AS13)
		II30	Historical Change Data Import (AS14)
Base Model	Function Scope	II31	APVA in Database
		II32	LTPA in Database
		II13	Purchase Fineplanning in Database
	Function Development	II12	Versioning
		II27	Calibration of Change Costs for APVA
Application	Application Scope	II08	APVA: Explorative Planning
		II09	APVA: User Training System
		II11	APVA: Automated Monitoring
	Application Type	II03	APVA: Allocation Planning for Multiple Echelons
		II05	APVA: Reconfiguration Extension
		II06	APVA: Area Planning Extension
		II14	Purchase Fineplanning: Supplier Price Scenarios
		II07	APVA: Dynamic OEE
		II10	APVA: Interactive DoE
		II33	APVA: Enhanced Error Correction
	Application Creations	II01	Multi-Echelon Network Configuration
		II02	Purchase Fineplanning
		II04	Long-Term Planning Assistant

5.5.2.2 Selection of Development Roadmap

After creating the development portfolio, the most suitable development path needs to be determined. For this, the primary benefits realised by application-level developments and secondary benefits realised through the fulfilment of dependencies are assessed. To assess the time to complete development, development resources are determined, and capacities are assigned to each implementation item. In this use case, the relevant resources include researchers, application developers, and various user and stakeholder groups. Using the dynamic TOPSIS prioritisation, the most suitable candidate is chosen. Figure 5-7 illustrates the available options analysed in the validation case regarding expected values. $\iota^{(DYN)} = 0.1$ and $\Delta\theta^{(REAL,REF)} = 1d$ are chosen for the dynamic discounting of options. The ordinate shows $\mathbb{E}\left[V_{\Lambda^{(IS)}}^{(DYN)}\right]$ and the abscissa displays $\mathbb{E}\left[\Delta\theta_{\Lambda^{(IS)}}^{(REAL)}\right]$. The iso-lines for $\mathbb{E}\left[\dot{V}_{\Lambda^{(IS)}}^{(DYN)}\right]$ indicate constant selection priority[64]. Iso lines for $\mathbb{E}\left[V_{\Lambda^{(IS)}}^{(STAT)}\right]$ indicate the static value of a development option. The figure only displays roadmaps with a risk preference range larger than $10°$.

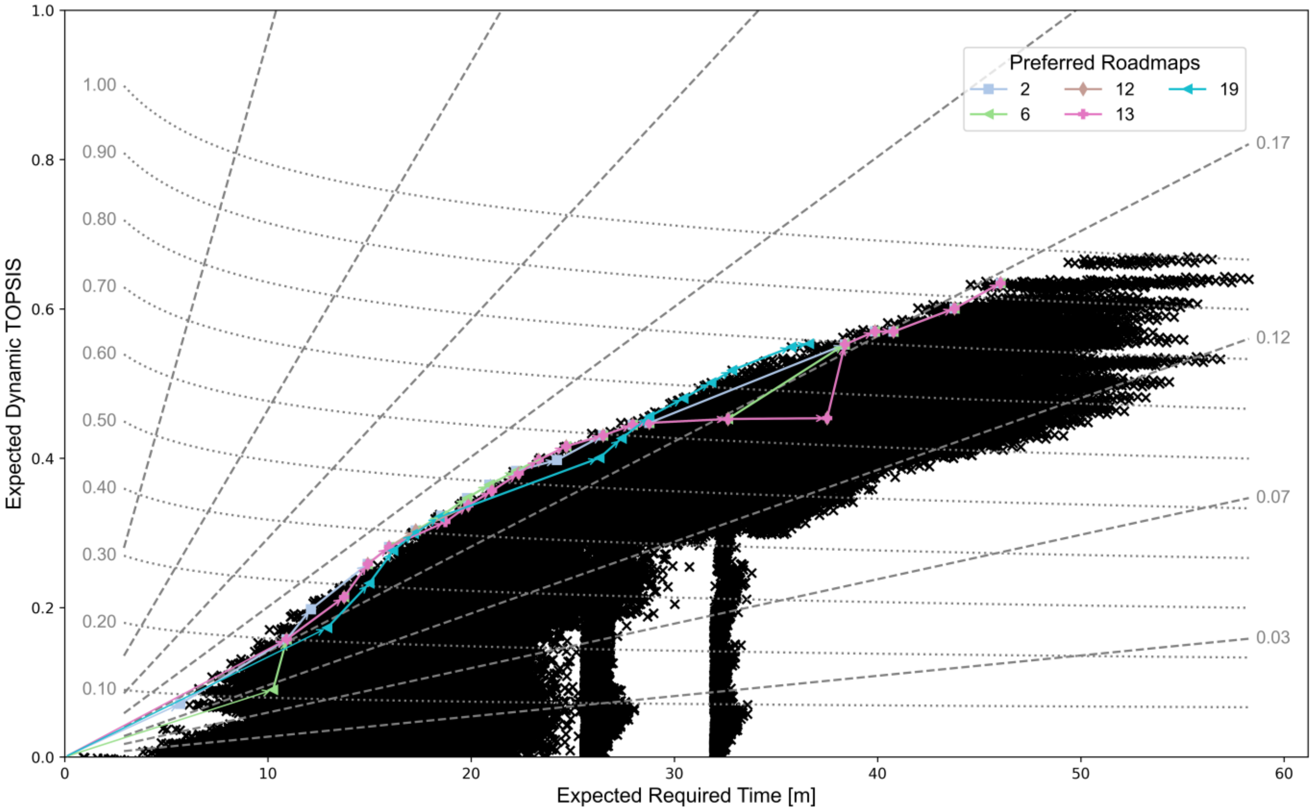

Figure 5-7: Scatter Plot of Available Development Options and Associated Value

Each development option contains several implementation items that contribute to it. Based on this, development roadmaps $\vec{\Lambda}^{(IS)}$ are chosen, which maximise $\mathbb{E}\left[\dot{V}_{\Lambda^{(IS)}}^{(DYN)}\right]$ throughout the framework development. Each $\vec{\Lambda}^{(IS)}$ represents an ordered set of development options $\Lambda^{(IS)}$. The expected value for each $\Lambda^{(IS)}$ is calculated using MCS with

[64] The values are given as $[a^{-1}]$.

$N^{(EXP)} = 10^4$[65] experiments, based on assumed benefit and required capacity distributions. The iterative development algorithm finds $N^{(DO)} = 5.1 * 10^5$ distinct development options when choosing from $N^{(AII)} = 32$[66] available implementation items[67]. The MCS not only results in an expected values, but also rate deviations $\varsigma\left[\dot{V}_{\Lambda^{(IS)}}^{(DYN)}\right]$ as displayed in Figure 5-8, which shows a scatter plot of all considered combinations across both.

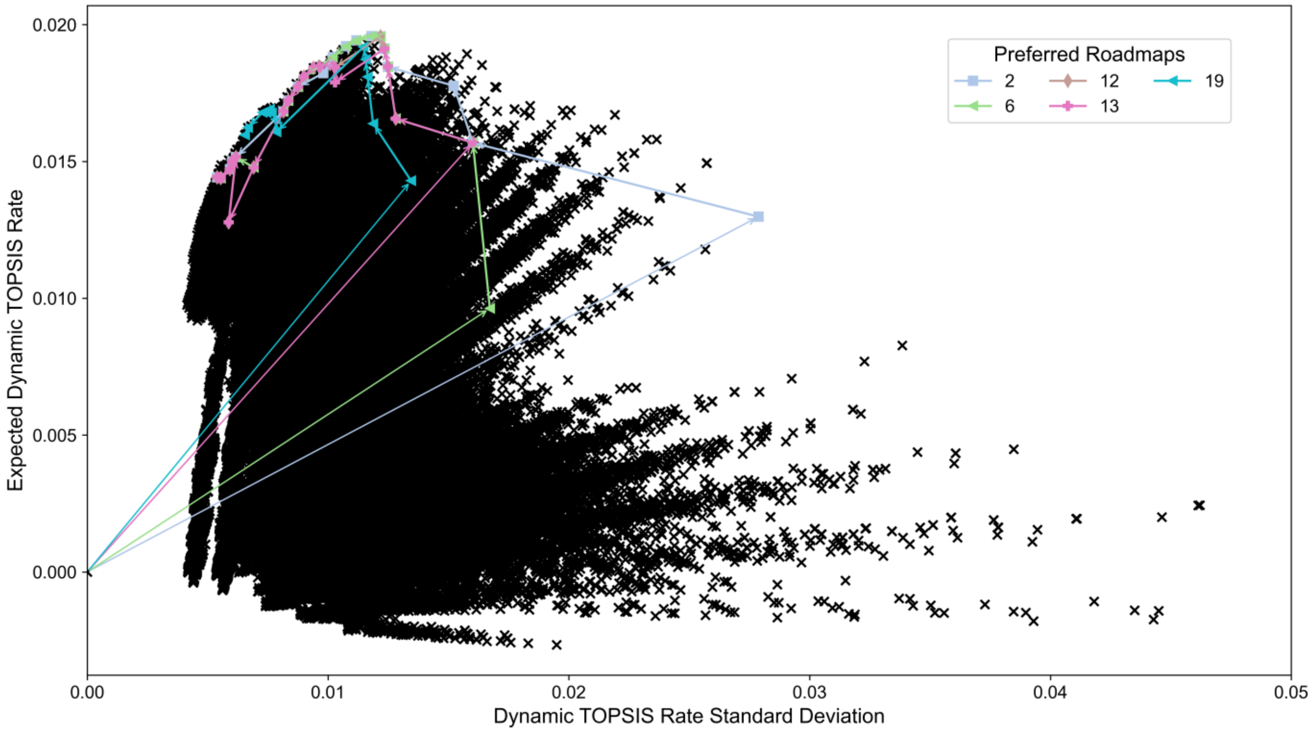

Figure 5-8: Scatter Plot of Development Options

Figure 5-8 also shows a set of development roadmaps, chosen to accommodate the different risk preferences of decision-makers. These development roadmaps are detailed further in Figure 5-9, depicting the range of risk preferences the roadmap dominates on the abscissa and $\mathbb{E}\left[V_{\Lambda^{(IS)}}^{(STAT)}\right]$ for the included combinations $\Lambda_i^{(IS)}$ on the ordinate.

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[65] Utilising the average standard deviation of $\bar{\varsigma}\left[V_{\Lambda^{(IS)}}^{(STAT)}\right] = 0.21$ and $\bar{\varsigma}\left[\Delta\theta_{\Lambda^{(IS)}}^{(REAL)}\right] = 10.67m$ an accuracy of $\epsilon\left[V_{\Lambda^{(IS)}}^{(STAT)}\right] = 0.0064$ and $\epsilon\left[V_{\Lambda^{(IS)}}^{(STAT)}\right] = 0.32m$ can be expected for a z-score of 3 for the MCS.

[66] As indicated above, only a selection of the implementation items is conceptualised to the extend necessary for this analysis. Furthermore, for high $N^{(AII)}$ the calculations become prohibitively intensive.

[67] The chosen process is iterative, thus only a fraction of the overall feasible options is considered. This can be observed in the space at the bottom right of Figure 5-7, where otherwise additional development options would reside.

Here a risk affine roadmap with risk angle $\zeta = 0°$ is solely focused on optimising $\dot{V}_{\Lambda^{(IS)}}^{(DYN,OPT)}$ whereas $\zeta = 90°$ marks a singular focus on $\dot{V}_{\Lambda^{(IS)}}^{(DYN,PES)}$.

In total, 19 distinct roadmaps are found. Upon closer inspection, a relatively consistent family of more risk-affine roadmaps spanning $\zeta \in (0°, 75.75°)$ is apparent. These roadmaps all end in $\Lambda^{(IS)} = 489{,}092$ or $\Lambda^{(IS)} = 489{,}096$, which are similar in terms of $\mathbb{E}\left[V_{\Lambda^{(IS)}}^{(STAT)}\right] = 0.93$. Depending on the chosen risk preference, the exact development path differs. For $\zeta > 75.75°$, a risk-averse set of roadmaps is preferred, which favour implementing fewer items and terminate earlier and at a lower $\mathbb{E}\left[V_{\Lambda^{(IS)}}^{(STAT)}\right] = 0.79$.

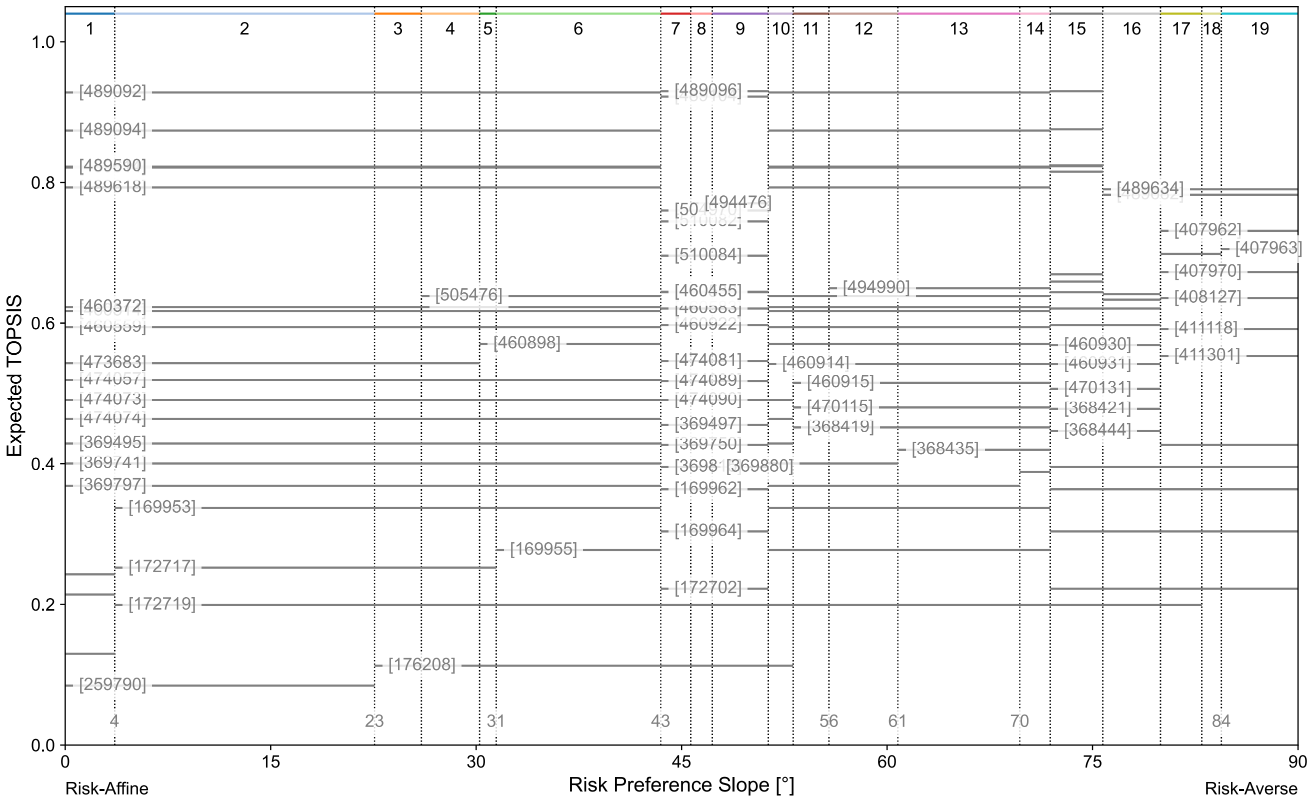

Figure 5-9: Implementation Roadmaps Across Risk Preference Range with Expected Static Utility of Included Combinations

Three sets of items can be distinguished, that are either part of every roadmap $\lambda^{(IS)} = (1, 2, 3, 4, 5, 6, 7, 8, 12, 16, 17, 19, 21, 22, 25, 26, 28, 30, 31, 32, 33)$, part of some roadmaps $\lambda^{(IS)} = (11, 20, 23, 24, 27)$ or never implemented $\lambda^{(IS)} = (9, 10, 13, 14, 15, 29)$[68]. Figure

[68] $\lambda^{(IS)} = 18$ is APVA, which is already implemented at the start.

5-10 shows the times at which items are realised in the roadmaps. The deviating roadmaps in the risk-affine family, $\vec{\Lambda}^{(IS)} = (7, 8, 9, 15)$ do not implement $\lambda^{(IS)} = 24$, which is a manual acquisition of station capabilities and implement the automatic version $\lambda^{(IS)} = 26$ instead. The other risk-affine roadmaps implement $\lambda^{(IS)} = 26$ as a replacement for $\lambda^{(IS)} = 24$ later. Thereby $\vec{\Lambda}^{(IS)} = (7, 8, 9, 15)$ has a slightly lower utility throughout but ultimately arrives at a slightly higher utility slightly earlier. The risk averse roadmaps omit items $\lambda^{(IS)} = (11, 20, 23, 24, 27)$, which are APVA based monitoring, several import functions and a calibration function.

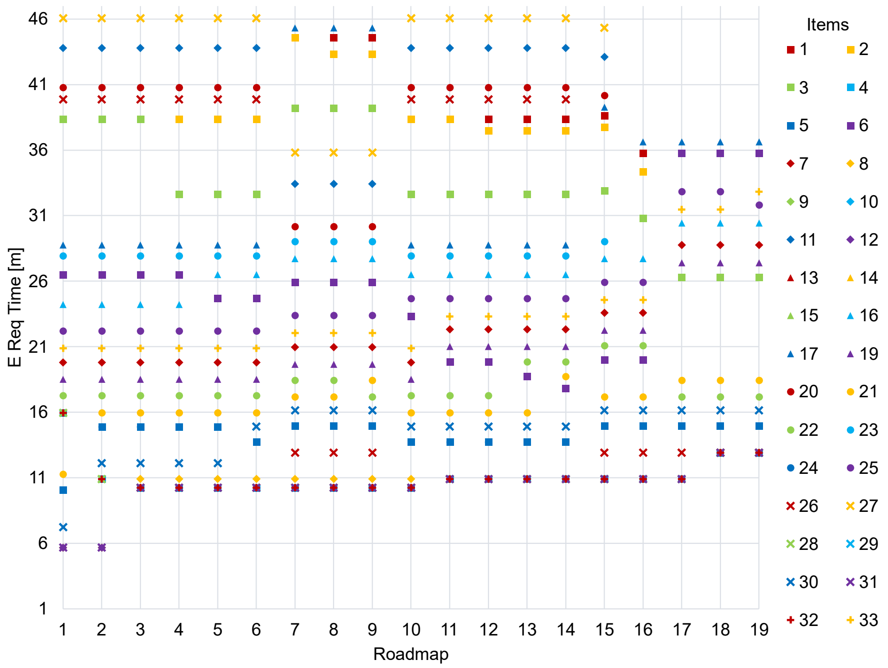

Figure 5-10: Realisation Time of Implementation Items Across Implementation Roadmaps

LTPA ($\lambda^{(IS)} = 4$), the DB versioning ($\lambda^{(IS)} = 12$) and the DB itself ($\lambda^{(IS)} = 31$) are part of every roadmap and are always implemented before $\theta^{(REAL)} = 16m$. A more detailed discussion of the implementation roadmaps is provided in Appendix A11.4.

In accordance with these results, the database, versioning and LTPA are implemented.

6 Discussion

This penultimate chapter situates this work within the broader context of current research. To this end, Section 6.1 discusses the results of the application in Chapter 5 and contextualises their contribution to validating the design framework introduced in Chapter 4. Section 6.2 reflects the merits of the proposed solution concept concerning the evaluation criteria and research question introduced in Sections 3.1 and 3.3.2 and the formal criteria introduced in 4.1.1. It also highlights and discusses the advantages and limitations of the proposed solution. Finally, Section 6.3 outlines future research directions.

6.1 Result Discussion

The results of this work originate from applying the framework to two PNC tasks of an automotive supplier, as described in Chapter 5. The results correspond to the PRQs and include DSS design, a shared data and function architecture, data acquisition options, and a comprehensive development portfolio for this GPN DT. In the following, the most noteworthy aspects of the validation are contextualised and evaluated.

The APVA design was primarily conducted before this work. It is thus used to test and validate the design process described in 4.2. The developed model exhibits overall high agreement with the design proposals resulting from the procedure. Specifically, choosing a primarily prescriptive model and the selected complementary methods agree with the overall framework. Differences, such as a shorter proposed time horizon, can be attributed to the procedural setting of the method.

The LTPA DSS is designed using the framework, serving as an experimental trial of the methodology. Based on the analysis of influences, a semi-prescriptive approach is chosen, which remains practical even when further applications, such as site consolidations, are considered. The DSS also highlights the importance of considering the relationship between multiple models, as the existence and availability of APVA significantly influence the design. This influence significantly alters the decision sets, as investment decisions are not required to be included in the LTPA model, which focuses on secondary capacities. LTPA also shows the need for a suitable specification, particularly in terms of delimitation, as data are required to enable the complete modelling of site capacity demands. Finally, the calculation of area demonstrates a particularity of different model expressions. The chosen linear consideration of area is simplistic and only provides approximate results. However, the data demand and model complexity rise drastically with any reasonable alternative, considering the geometric shapes of the area demand and offer. This aspect highlights the need for models with lower AC, where imprecision may be overcome through a more thorough, manual investigation of available options.

The design of LTPA highlights the importance of multi-model interactions and the deliberate design of such multi-model systems. The successful development of LTPA underscores the applicability of the proposed method for describing and designing such systems. However, it cannot encompass all aspects of the method. Even when model creators apply the method, significant design freedom remains in their hands. This freedom and the requirement for expertise are unlikely to be entirely superseded by a formalised procedure. Nevertheless, systematising the interactions between models and adapting them accordingly proves crucial for the design of LTPA.

The validation case highlights the applicability of the proposed DT architecture as a suitable joint DM for multiple DSSs that have been developed. This model originates from a comprehensive consideration of various PNC tasks and is specifically tailored to align with the company's existing DM. The DB uses the proposed versioning concept to accommodate and integrate uncertain data from several sources. It shows that the concept that advances DBs in their applicability to distributed planning applies to commonly used DBs. It enables the utilisation of a single DB by multiple models, users, and corresponding planning processes with scenarios while facilitating the integration of various data sources.

The overall architecture of the DT is comparable to other IT architectures, which also form distinct layers responsible for different functions. The validation case shows that the concept has merit, as an independent integration of multiple DSS is possible, and synergies between the DSS arise. However, it also shows some of the limitations of the approach. For example, a DSS like LTPA can require data preprocessing steps. These steps can be implemented outside the DB, but in some cases, creating application-specific interfaces within the DB is more suitable. Therefore, the DB will always be adapted to the present set of DSSs and, more broadly, applications.

The validation achieves only limited progress in terms of model calibration and validation. As most parameters of the utilised models concern static characteristics of the system, a higher priority is placed on the quality and availability of those data. However, dynamic factors, such as setup times, scaling factors, and others, play a crucial role in PNC tasks. Thus, additional attention may be paid to specifying calibration and validation schemes for PNC tasks.

The approach to data acquisition is only tested to a limited degree in the validation case. Particularly in organisations with established planning processes, the relevant data sources should be mostly known before creation. They should also be available at a suitable level of abstraction and with adequate quality to limit the number of transformation steps. As this cannot be expected of non-established planning processes, further validation of the approach is necessary. However, the realised data acquisition strategies and the designed portfolio indicate the general suitability of the approach.

Integrating the proposed DT in an organisation is a considerable task that depends on several factors. The validation case demonstrates that both the application classification and the implementation scheme are applicable and extend the range of possible values offered by the DT. The implementation roadmap design is applied in the validation case, helping to systematically select suitable modules for the digital twin while considering available development resources and the organisation's priorities. It makes the complex problem of prioritising all the different development options available in the design framework solvable and provides estimates for both improvement potential and the associated risks. Iterative reuse of this planning approach should help align and update development paths.

6.2 Critical Reflection

The central research question (RQ) of this work is:

How can DSSs for the configuration of GPN be realised efficiently, requiring reduced efforts for each decision and thus enabling faster and better decision-making?

To investigate this RQ, several partial objectives are pursued. Recognising the heterogeneity of PNC tasks and the need for apt decision support, a systematic design approach for DSS is developed. The approach structures contextual dimensions of the examined decision type and produces a systematic structure for methods in relevant DSS. A procedure to create a suitable DSS is developed, which addresses the dependencies between the dimensions of the decision tasks and the methods while minimising the development efforts. Finally, recognising the dependencies between multiple DSSs as part of a unified DT, an extension is created to address multi-DSS design systematically. The developed approach effectively supports the design of suitable DSS for multiple PNC tasks by considering various available methods. It thus represents a step forward from most existing approaches, which are either tailored to a particular style of DSS or provide only very general, open support for DSS design, relying heavily on expert developers. The addition of multi-model design also represents a novel contribution to the knowledge of DSS development.

The following partial objective is the creation of a unifying architecture that effectively utilises synergies between multiple DSSs, thus increasing functionality and lessening development and data acquisition efforts. The DT architecture has three layers: data sources, the base model, and applications. At the core of the DT is an extendable DB structured according to a shared DM. This DB implements versioning for uncertain developments and multiple perspectives. In addition, general calibration schemes are devised. Finally, the design decisions in model generators are structured and defined. The architecture features a DM adaptable to different organisations, data sources, and PNC tasks, which can be supported suitably. It allows for generating application model instances and supports them with additional functionalities. This work provides the theoretical framework for those aspects, whereas the implementation still depends on the organisation employing it.

The third objective is to ensure the systematic and comprehensive acquisition of data. This work establishes a catalogue of relevant data sources and their potential uses. It further defines data acquisition strategies, along with suitable preprocessing methods, which are chosen based on the demands and the quality of the data. Relevant costs for acquisition strategies are systematised, and a procedure is devised to derive the benefits of the strategies based on their contribution to the DT. To realise the data acquisition strategies, the individual conditions of the organisation still need to be considered. Furthermore, manual data inputs remain essential for some aspects of PNC models.

The final objective of this work is to fit the DT to the employing organisation and create a development path that ensures a positive contribution to the organisational performance. This work introduces an extended application classification going beyond typical planning applications. A development procedure is created based on this classification and the previous partial objectives. It begins with initial model development and then branches into several development directions. A dynamic TOPSIS approach is utilised to choose the most suitable direction for the organisation. With this, the DT can be adapted to the specific needs of an employing organisation while ensuring a positive contribution to organisational performance.

As shown in Figure 6-1, this work fulfils the requirements for a solution as defined in 3.1. It also adheres to the formal requirements outlined in 4.1.1 and shows that a system for decision support in PNC tasks can be created as stipulated in the research hypothesis.

Requirements ○ Not met ◔ Slightly met ◑ Partially met ◕ Mostly met ● Entirely met	Decision support			Model architecture				Data acquisition			Organisational integration			
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
	Comprehensive PNC Task Representation	Comprehensive Model Type Representation	Systematic Method Design	Adaptable Base Structure	Supports Diverse PNC Tasks	Extended Model Functions	Model Generation	Identification of Suitable Data Sources	Data Acquisition Methods	Data Preprocessing Methods	Company Specifics Requirements	Diverse Application Forms	Effort-Benefit Consideration	Implementation Procedure
Solution Approach	●	●	●	●	●	●	●	◕	●	●	◕	●	●	●

Figure 6-1: Assessment of the Solution According to the Requirements

While the above shows that this work fulfils the requirements, some limitations remain. In some cases, ad-hoc DSSs built on table-based programs such as Excel may be a more economical and quicker solution to implement. This work does not consider which type of development environment for DSS is most suitable and where the transition points from more flexible systems to more rigid DBs lie. The work also does not consider APSs in detail, some of which can be used as ready-made PNC task DSSs. Often, these commercial solutions already integrate with the organisation's ISs. However, they typically leave much less design freedom for organisations and have yet to see broad-scale adoption in more long-term decisions, specifically when focusing on configuration decisions. Finally, creating a DT based on this work may induce additional planning complexity and create undesired information exchange in the organisation, which this work does not fully address.

This work is set apart from previous approaches by the combination of specificity for PNC tasks, consideration of multi-model systems and adaptability of the resulting DT. In particular, the systematic approach to DSS design is a unique contribution. The extension to multi-model systems and the derivation of suitable strategies for multi-model designs are also unique in the PNC literature. The architecture's adaptability to various DSS, particularly its unique versioning concept for a multi-source planning DB, should be highlighted. Finally, the open yet systematic consideration of several development directions as a compromise between short-term advantages and long-term development is a noteworthy addition to the extant knowledge.

6.3 Outlook

Despite the relatively broad scope of this work, several areas remain for further research and exploration.

Firstly, the concepts and classifications developed systematically in Chapter 4 could only be validated to a limited degree. Examining additional use cases at the company, as well as others, may lead to further insights and improvements.

Secondly, though this work contains substantial efforts to standardise models while maintaining a degree of specification for the individual tasks, additional steps may be taken. This standardisation may involve specifying the semantic characteristics of different DSSs in a more unified form to reduce the integration effort for additional DSSs. Promising approaches towards this are currently pursued in AAS (Behrendt, & Martin et al., 2023).

The concept of a daydreaming factory, defined by Nassehi et al. (2022), has been considered in this work, particularly concerning model interactions. However, the design of DSS capable of performing learning processes on unlikely events has been largely overlooked. Future work may examine the design of such systems in the context of GPN more closely and develop the software necessary to perform capacity-based experiment scheduling across multiple perspectives.

The validation case has shown that a substantial aspect of application design in adapting DSS for specific user groups lies in user interfaces and the specification of degrees of freedom users are given. Future research may also explore designing systems that are more adaptable to the needs of different users, while relying on the same underlying methods for DSS design.

One of the central shifts currently underway in production management and control is the proliferation of approaches using machine learning (ML) algorithms, primarily discussed under the umbrella of artificial intelligence (AI). To date, the relative scarcity of data and relatively long available decision times have limited the applications of AI in PNC tasks. This work only considered AI approaches in terms of prediction methods for external factors and surrogate models for computing-intensive predictive and prescriptive models. However, with increasingly powerful AI tools that cut across multiple domains, new approaches to PNC may emerge. For example, approaches may infer set-up times and costs specific to a production process based on training across numerous industries and organisations. AI and, more specifically, large language models may also become the interface between specialised predictive and prescriptive models and users, as they provide a flexible platform adaptive to their users' model and system expertise.

7 Conclusion

Model-based decision support systems for production network configuration have garnered prolonged interest in academia, and numerous case studies of applications are available. The motive behind their application seems clear: configuration decisions are inherently complex, and considering uncertainty in them is only possible with computerised help. Nevertheless, the permeation of such tools in producing companies remains limited today. Anecdotally, established tools are already being abandoned in favour of more manual decision-making. This hesitancy may be costly in an increasingly connected world, where speed and accuracy of decision-making can be essential competitive factors. With improved computing power at low costs, the concept of a digital twin as the virtual model connected to its real-world counterpart through continuous data synchronisation has emerged. In many domains, the adoption of this concept is growing. However, decision support systems for production network configuration seem to be used too infrequently to be economically transformed into digital twins, particularly considering the heterogeneity of configuration tasks.

This work presents an integrated approach to creating a digital twin for production network configuration. This approach facilitates faster and more accurate decision-making and is economically viable. It is designed to maximise synergies between different configuration tasks while also allowing for adaptation to the specific needs of the task and the organisation through a three-layer structure. A systematic design process for decision support systems in configuration tasks is established by considering the suitability of different methods used in such systems, the dependencies between them, and the characteristics of the configuration task. The resulting process minimises the effort to develop a fitting decision support system. An amendment to the process allows for the integration and interaction of multiple models. While the decision support systems are tailored for specific tasks, a base model layer provides commonality. A common database built on a shared data model forms the core of the base model. This data model enables the distributed planning of multiple decision support systems and users through a comprehensive versioning concept. Additionally, shared functions such as calibration and automatic model generation are provided here. To acquire data for the decision support systems, relevant data sources are characterised, a framework for data collection and preprocessing is developed, and an assessment scheme is contrived. Finally, to facilitate the adoption of the approach, additional application types are characterised, broadening the utility of individual decision support systems, and a structured implementation process is designed to balance the long-term value with the short-term utility of the decision support systems.

The developed approach is applied practically at a large automotive supplier. An existing system for production volume allocation and investment planning serves as the starting point for the development. The digital twin is built around this decision support system, and a second system is designed to support the related long-term site planning process. This use case demonstrates the applicability of the overall approach. It shows that a digital twin of the production network can be developed iteratively, and synergies between different tasks can be leveraged. In conclusion, this research successfully addresses the research question and contributes to more reactive and better decision-making in global production networks.

Future research can build upon these findings in various ways. Particularly, consecutive works could test the approach in additional use cases to further refine it. Additional standardisation and semantic relations between information models may enable the integration of even more unstructured data today into the database. Additional research may delve deeper into daydreaming models and enhance user integration even further. Finally, future work may integrate artificial intelligence into production network models to unlock more intuitive decision-making and allow decision-makers a comprehensive understanding of the global production network.

Own Publications

Benfer, & Autenrieth et al., 2022

Benfer, M., Autenrieth, M., Brützel, O., Grützner, H., Peukert, S., & Lanza, G. (2022). Agile Erstellung von Materialflusssimulationen. *Zeitschrift Für Wirtschaftlichen Fabrikbetrieb*, *117*(12), 867–871. https://doi.org/10.1515/zwf-2022-1158

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Figures

Tables

Equations

Appendix

A1 Methods in DSS

In the following, relevant methods typically constituting DSS are introduced. These methods will be used to design DSS specifically for the purposes of the employing company. Many of these methods originate in Operations Research (OR), a discipline of science principally interested in using mathematical models to describe and improve operational and logistical challenges across numerous fields of application. This section structures the available methods based on their potential use in DSS. This includes predictive, configurative, prescriptive methods, decision-making and scenario generating methods and finally meta models.[69]

A1.1 Predictive Models

In the following, prevalent predictive models relevant to decision-making in GPN are introduced. Predictive models serve to represent the behaviour of GPNs under a variety of circumstances. In many cases, GPN can be modelled with relatively simple linear or mixed integer linear models, but some circumstances may require more complex time-variant models.

Linear Models

Linear models are the simplest models to predict the behaviour of production networks. They can generally be expressed as follows[70]:

$$\boldsymbol{f}(\boldsymbol{x}) = \boldsymbol{C}\boldsymbol{x} \mid \boldsymbol{x} \in \mathbb{R}^n, \boldsymbol{C} \in \mathbb{R}^{k \times n} \qquad \textit{Equation A 1}$$

$$\boldsymbol{A}\boldsymbol{x} \leq \boldsymbol{b} \mid \boldsymbol{x} \in \mathbb{R}^n, \boldsymbol{b} \in \mathbb{R}^m, \boldsymbol{A} \in \mathbb{R}^{m \times n}, \boldsymbol{x} \geq \boldsymbol{0} \qquad \textit{Equation A 2}$$

where Equation A 1 describes the target function and Equation A 2 the boundary conditions. Linear models are very limited in terms of their ability to capture the behaviour of complex systems. In some particular cases, nonlinear behaviour can be approximated in a piecewise linear model, provided the to-be-approximated function is unidimensional and convex. However, linear models are uniquely suited to be used in prescriptive models as they can generally be solved in polynomial time. (Domschke, & Drexl et al., 2015a, p. 21)

[69] In the following, several methods are introduced and described using conventional equations that encapsulate them. To avoid over-specifying variables no global symbol index is given for this appendix. Instead, variables are explained in the text concerned with them.
[70] Note that this formulation has a multidimensional target function, formulations with a scalar target function are common though.

Mixed Integer Linear Models

Mixed-integer linear models reflect the inherent granularity of many decisions in production network configuration, for example only whole machines may be bought and sites may only be operating or not operating. They follow equations Equation A 1 and Equation A 2 with the restriction, that some $x_i \in \mathbb{Z}$. Though they cannot generally be solved in polynomial time, many heuristics to solve them are available. Mixed integer linear models are particularly suited for problems in production networks, as many of the behaviours of those systems are well described by those models. (Domschke, & Drexl et al., 2015d, 127ff)

Mixed integer models can also be used to approximate a wide range of nonlinear functions. This linearisation is usually piecewise. However, linearisation comes at the expense of adding additional complexity in the form of control variables and boundary conditions. A common procedure for piecewise linearisation of both continuous functions and statistical data points are multi adaptive regression splines (MARS) (Friedman, 1991). Using MARS, even multidimensional nonlinear functions can be linearised to be used in MILP.

Quadratic Models

Quadratic models can generally be stated as follows[71]:

$$f(\boldsymbol{x}) = \frac{1}{2}\boldsymbol{x}^T\boldsymbol{Q}\boldsymbol{x} + \boldsymbol{c}^T\boldsymbol{x} \mid \boldsymbol{x}, \boldsymbol{c} \in \mathbb{R}^n, \boldsymbol{Q} \in \mathbb{R}^{n\times n}$$ *Equation A 3*

$$\boldsymbol{A}\boldsymbol{x} \leq \boldsymbol{b} \mid \boldsymbol{x} \in \mathbb{R}^n, \boldsymbol{b} \in \mathbb{R}^m, \boldsymbol{A} \in \mathbb{R}^{m\times n}, \boldsymbol{x} \geq \boldsymbol{0}$$ *Equation A 4*

These models are more complex to solve prescriptively than linear models and only play a subordinate role in production network configuration, as the behaviour of those systems can typically be adequately captured using mixed integer linear models. (Domschke, & Drexl et al., 2015e, p. 202)

Stochastic models

Whereas deterministic models assume that all information describing a problem is known at decision time, stochastic models incorporate uncertainty in the form of variables unknown at decision time. A typical instance is a two-stage stochastic model:

$$f(\boldsymbol{x}) = \boldsymbol{c}_1^T\boldsymbol{x}_1 + \mathbb{E}_{\boldsymbol{\psi}}[\boldsymbol{c}_2^T(\omega)\boldsymbol{x}_2(\omega)]$$ *Equation A 5*

[71] In this case using a scalar target function and linear constraints

$$\boldsymbol{A}_1\boldsymbol{x}_1 \leq \boldsymbol{b}_1 \mid \boldsymbol{b}_1 \in \mathbb{R}^{m_1}, \boldsymbol{A}_1 \in \mathbb{R}^{m_1 \times n_1} \quad \textit{Equation A 6}$$

$$\boldsymbol{A}_{21}(\omega)\boldsymbol{x}_1 + \boldsymbol{A}_{22}(\omega)\boldsymbol{x}_2(\omega) \leq \boldsymbol{b}_2(\omega) \mid \boldsymbol{b}_2 \in \mathbb{R}^{m_2}, \boldsymbol{A}_{21} \in \mathbb{R}^{m_2 \times n_1}, \boldsymbol{A}_{22} \in \mathbb{R}^{m_2 \times n_2}, \quad \textit{Equation A 7}$$

$$\boldsymbol{x}_1, \boldsymbol{x}_2 \geq \boldsymbol{0} \mid \boldsymbol{x}_1 \in \mathbb{R}^{n_1}, \boldsymbol{x}_2 \in \mathbb{R}^{n_2} \quad \textit{Equation A 8}$$

where $\omega \in \Omega$ is a realisation of the uncertainty with probability $\mathbb{P}(\omega) \neq 0$, and $\mathbb{E}_{\boldsymbol{\psi}}$ is the expected value function based on the random vector $\boldsymbol{\psi}: \Omega \to \mathbb{R}^{n_2+m_2(n_1+n_2+1)}$. In this type of problem $\boldsymbol{x}_2$ is chosen after the realisation of ω, which is called recourse. (Nickel, & Rebennack et al., 2022, pp. 296–297)

Several behaviours in production systems can be described as queuing systems, which are described by random variables $y(t) \in Y$ to describe the state of a system. Systems with countable state spaces Y, where:

$$y \sim Exp(\zeta_y) | 0 \leq \zeta_y < \infty \quad \textit{Equation A 9}$$

$$0 \leq l_{y_1,y_2} \leq 1 | \sum_{y_1,y_2 \in Y, y_1 \neq y_2} l_{y_1,y_2} = 1 \quad \textit{Equation A 10}$$

are called Markov processes. Here l_{y_1,y_2} describe the transition probability from y_1 to y_2. Markov processes can be used to describe complex queuing systems as they allow for the immediate calculatio of system characteristics such as waiting times. (Nickel, & Rebennack et al., 2022, pp. 387–401)

A common way to capture order processing are Jackson Networks, which are a stochastic queuing network that assume Poisson intervals for arrivals[72]. They are analytically tractable, which can be beneficial when trying to find optimal solutions. (Nickel, & Rebennack et al., 2022, 403ff)

Simulation

Simulation is understood as the “representation of a system with its dynamic processes in an executable model to reach findings, which are transferable to reality. […] In the broader sense, simulation refers to the preparation, execution, and evaluation of targeted experiments with a simulation model.” (VDI, 2014, p. 3). Simulation is often used synonymously with predictive models, though it deviates due to the emphasis on dynamic processes (VDI, 2014, p. 3). Commonly used simulation models can be

[72] For example, arrival of customer orders and services.

categorised as discrete event simulations (DES), agent-based simulations (ABS), system dynamic (SD) simulations, and dynamic system (DS) simulations (Borshchev & Filippov, 2004). DS simulation models commonly employed in product or process design like finite element, finite volume, and rigid body simulations are not relevant for this work and will not be considered further.

As dynamic processes of complex systems are often difficult to calculate analytically, simulation models discretise time, thus transforming analytical functions into numerical ones. Due to their dynamic nature, simulation models necessarily contain both state and flow variables.

Discrete Event Simulation
DES discretises time into non-uniform steps between events. In DES, changes to the system state can only occur at events. Events are typically scheduled at runtime in a global event queue. DES is particularly suitable for systems of discretised nature or systems that are closely resembled by discrete models. DES often incorporates a degree of stochasticity, both in terms of the state change equations and the event scheduling. (Domschke, & Drexl et al., 2015b, p. 235)

System Dynamics
SD fundamentally model complex systems by numerically solving differential equations. In those systems, the state of the system directly influences the change in state or flow. SD is well suited to systems that are governed by continuous or near continuous flows. In GPN, SD is typically used to capture broad flows of goods and model strategic aspects like risks. (Domschke, & Drexl et al., 2015b, pp. 235–236)

Agent Based Simulation
Whereas DES and SD, represent processes within systems, ABS models the interactions between multiple independent agents. Each agent is modelled with a state, which may change depending on external inputs or scheduled events. ABS is particularly suitable for the representation of systems with actors with incomplete information and differing objectives. (Domschke, & Drexl et al., 2015b, p. 236)

A1.2 Configurative Methods

Configurative methods are concerned with the definition of alternatives in the decision. These methods are applied prior to predictive or prescriptive models and directly involve the DMC in varying degrees. Depending on the AC of the chosen model or models, configuration determines a specific set of alternatives, or the space alternatives originate from. A fundamental distinction in configurative methods is between (i) alternative creation in open, non-specified decision fields, (ii) alternative generation in roughly specified decision fields, and (iii) alternative search, in well-defined decision fields.

Creativity Techniques

Creativity techniques are used to systematically extract alternatives from human creativity in non-specified decision fields or roughly specified decision fields. The range of techniques available is quite prolific. Generally, they may be distinguished into broad, open idea generation, systematic alternative construction, and distributed expert mining. These techniques can also be combined with each other.

Idea Generation
These techniques seek to open the space of alternatives before judging them. Typically, the techniques are performed in groups. This encourages creative divergent solutions which can then be judged. Examples of this type of method are brainstorming, aiming to open up all possibilities, and brainwriting, which enables groups to build on each other's ideas. (Villiers, 2022, 199ff)

Systematic Alternative Construction
These techniques seek to systematically map the available options and structure the decisions. These techniques do not encourage "outside-of-the-box" thinking as much but instead ensure that the field of alternatives is filled consistently. Examples are a morphological analysis, that determines key alternative dimensions and tests combinations of those dimensions, and the Design Structure Matrix, which allows for a sub structuring of decisions to break them into smaller chunks (Eppinger & Browning, 2012, pp. 2–4).

Distributed Expert Mining
These methods are designed to harvest knowledge from several domain experts. They operate usually in an iterative fashion, so that knowledge can diffuse between experts. Examples are the Delphi-Technique, which uses iterative questionnaires and anonymised feedback (Linstone & Murray Turroff, 1975, pp. 3–4), and nominal group technique, which utilises a round-robin sharing of ideas and avoids senior-person biases (Harvey & Holmes, 2012).

Design of Experiments

In well-defined decision fields, the generation of configurations is largely an issue of efficiently examining the range of options as each examined configuration is associated with decision-maker and computational effort and time spend. For these statistical methods developed under the term design of experiments (DoE) may be used. Herein, DoE prescribes the selection of a range of input parameters $\boldsymbol{x} \in X_s^{(IP)}$ to best characterise the behaviour of the system s with the behaviour $\boldsymbol{f}_s(\boldsymbol{x}) = \boldsymbol{y}$, where $\boldsymbol{y}$ denote the response of the system. A number of experimental designs can be used. Full factorial designs examine all possible combinations of factors (Antony, 2014, p. 67). Fractional factorial designs only study a subset of factor combinations and are particularly suitable if higher order interactions between factors can be ruled out (Siebertz, & van Bebber et al., 2017, p. 28). Central composite designs examine changes to single factors on multiple levels around a centre point and are suitable to study non-linear effects (Siebertz, & van Bebber et al., 2017, p. 40 ff.). Space-filling-designs (SFD) can be used to create realistic synthetic datasets, for example for meta-modelling (Siebertz, & van Bebber et al., 2017, p. 231). Examples of SFD are the Latin-Hypercube-design, Monte-Carlo-Sampling or Uniform-design (Siebertz, & van Bebber et al., 2017, p. 226).

Constraint & Objective Variation

When a prescriptive model is used in well-defined decision fields, the users are typically provided a single "best" decision for their objectives. To purposefully create additional options, several techniques can be used. These techniques align closely with the sensitivity assessment, post-optimality, and multi-objective decision-making.

Parameter & Sensitivity Exploration

Using post-optimality analysis and or sensitivity analysis the importance of parameters for specific decisions is evaluated. This is then used to redesign constraints. For example, an indication that a decision to open a new site is mainly driven by capacity restrictions, may lead to allowing a capacity extension at an existing site as an alternative.

Pareto Front Exploration

Uses multi-objective decision-making techniques[73] to establish the Pareto Front of preferred scenarios and analyses the resulting options closely. This allows decision makers to find noteworthy tipping points for decisions. These options are discussed in more detail in Appendix A1.4.

[73] The simplest way to do this is usually to solve the multi-objective optimisation as a weighted sum with different weights.

Constraint Relaxation
Reformulates constraints as elastic, i.e., adds penalised slack variables to allow solvers to “break” rules. This may help to identify issues in problem formulation or highlight areas that require attention.

A1.3 Prescriptive Models

Prescriptive models are used to determine preferred alternatives under given objectives and system characteristics. In the following the focus is put on single quantitative objective methods. Multi objective and multi attribute methods are discussed in Appendix A1.4.

Linear Programming

Linear models are uniquely suited for optimisation. In linear programming (LP) or linear optimisation any global optimum has to lie on a corner of the decision variable space $\mathcal{D}$. Algorithms like the original simplex algorithm and subsequent algorithms that are even more efficient take advantage of this characteristic to generally solve linear optimisation problems in polynomial time.

Mixed Integer Linear Programming

In mixed integer linear programming (MILP), the decision space $\mathcal{D}$ is not continuous, thus global optima typically lie somewhere on the inside. However, the similarity to LP can be used to efficiently calculate lower and upper bounds and to effectively structure the decision problem. Exact[74] algorithms to solve MILP or MIP more generally, can be categorised into decision-tree methods, sectional-plane methods, as well as combinations thereof (Domschke & Scholl, 2008, pp. 134–135). Decision-trees are further divided into complete enumeration, limited enumeration like branch and bound, and dynamic programming. In addition to these exact approaches, some heuristics serve as opening procedures, local search and improvement procedures, abandoned exact approaches, and combinations thereof (Domschke & Scholl, 2008, p. 135). In the following, noteworthy approaches are highlighted.

The branch and bound approach separates the problem and thereby the decision variable space $\mathcal{D}$ into subproblems that are disjunct and in sum cover all of $\mathcal{D}$. By calculating

[74] Exact algorithms here denote algorithms who can guarantee to find globally optimal solutions in contrast to heuristics.

upper bounds for relaxed variants[75] of each subproblem and branching whenever a subproblem is not efficiently solvable, sections of the decision tree can be excluded from consideration to solve the problem. (Domschke & Scholl, 2008, pp. 140–146)

The branch and cut approach generally uses a similar approach to branch and bound but limits the search space by "cutting" away parts of $\mathcal{D}$ that lie outside of the space of solutions that may not be accessed by integer variables through adding new boundary conditions. On this reduced search space the branch and bound procedure is then applied. (Domschke & Scholl, 2008, pp. 146–149)

Many of the here discussed approaches are integrated in commercially available solvers and thereby largely invisible to a user. Many of the current academic contributions, that advance PNC using MIP and MILP propose proprietary heuristics to solve particular problems faster than general solvers can (Melo, & Nickel et al., 2009, p. 408). However, development times for these particular solutions are much higher than using general solvers. Due to the specificity, the details of this consideration will not be further considered in this work.

Quadratic Optimisation

Rockafellar (1993, p. 185) argues that the "great watershed in optimisation" is not between linear and nonlinear, but between convex and nonconvex problems. In quadratic models such as described in Equation A 3 and Equation A 4 convexity is given if $\boldsymbol{Q}$ has only positive eigenvalues. In this case the problem can usually be solved relatively quickly with commercial solvers. When this is not the case the problem becomes NP-hard and requires distinctly higher solving times.

Stochastic Optimisation

Stochastic optimisation approaches acknowledge the stochastic nature of most real-world problems, as the development of a systems environment, the systems current state and the behaviour of a system cannot be fully known. Thus, stochastic optimisation focuses on the expected and possible outcomes of the available alternatives. Usually, stochastic optimisation requires the uncertainty to be represented in discretised scenarios with an assigned probability corresponding to the integral of the probability

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[75] Relaxation can typically be achieved by foregoing the integer condition (LP relaxation) or by replacing boundary conditions with suitable additions to the goal function using dual variable (Lagrange relaxation).

density function they represent. This discretisation can be achieved using fixed intervals or by utilising Monte-Carlo simulation and clustering for example.

Dynamic Programming

An approach to solve optimisation problems with multiple distinct stages $i \in I$ is called dynamic programming (DP) or dynamic optimisation. In DP, the decision strategy $\boldsymbol{x}$ is divided into a set of partial strategies $\boldsymbol{x}_i$, each of which is subject to its own optimisation problem. The approach is based on Bellman's optimality principle, which states that an optimal overall decision strategy $\boldsymbol{x}$ must be constituted by partial strategies $\boldsymbol{x}_i$ that transform the examined system s from a state $\boldsymbol{y}_i$ to $\boldsymbol{y}_{i+1}$ which are each also optimal with respect to that transformation (Bellman, 1957, p. 83). Following this notion, and given that the objective z of a strategy $\boldsymbol{x}$ may be expressed as

$$z(\boldsymbol{x}) = \min_{\{x_i\}i \in I}/\max \sum_{i \in I} \beta^i f(\boldsymbol{x}_i, \boldsymbol{y}_i) \qquad \textit{Equation A 11}$$

where $\beta \in (0,1)$ denotes the discounting factor, the Bellman equation states that (Domschke, & Drexl et al., 2015c, p. 172):

$$z(\boldsymbol{x}_i) = \min_{\boldsymbol{x}_i}/\max\big(f(\boldsymbol{x}_i, \boldsymbol{y}_i) + \beta z(\boldsymbol{x}_{i+1})\big) \qquad \textit{Equation A 12}$$

Thereby, large multistage optimisation problems can be divided into many partial problems, reducing the computational burden. These subproblems can then be solved sequentially. Typically, backwards induction is used, by which the optimal partial strategy $\boldsymbol{x}^*_{i,j_i}$ is found which transforms the system from a permissible state $\boldsymbol{y}_{i,j_i}$ to another permissible state $\boldsymbol{y}_{i+1,j_i}$ with the optimal overall expected value $z\big(\boldsymbol{x}_{i,j_i}\big)$. Since the state at the current time $\boldsymbol{y}_0$ is usually known, the overall optimal strategy is chosen with $\boldsymbol{x}^*_0$. DP can also be applied in stochastic problems.

DP can reduce computational complexity, especially if the number of states is limited and thereby the number of effectively redundant partial optimisation problems (Bellman, 1957, p. xi). The stages of DP problems are often used as periods, as they represent clearly sequential stages of a problem. However, other stage concepts such as production stages are also possible (Domschke, & Drexl et al., 2015c, p. 162).

Metaheuristics

Meta heuristics are non-problem specific heuristics to find optimal or preferable solutions to problems. As such they do not take advantage of the specific problem structure like some of the previous methods do[76] and they generally cannot guarantee exact solutions. In general, meta heuristics work by iteratively probing a predictive model with a set of parameters, assessing the solution quality[77] and then determining a new set of parameters to test. Broadly three categories of meta-heuristics can be distinguished, (i) population-based approaches, (ii) trajectory-based approaches, and (iii) hybrid approaches.

Population-Based Approaches
These approaches generate a population, i.e., multiple solutions at once that are then tested and assessed before a new population is generated. This scheme allows for solutions to be tested in a parallelised manner and to compare solutions to each other. Typical examples include genetic algorithms (GA)[78] and particle swarm optimisation (PSO). GA encode parameter sets as genes and create subsequent solutions based on random variation and recombination of individuals. PSO searches for best solutions in real-valued search spaces through a swarm of particles that update their velocity between each step based on each particles own previous best position and the swarm's overall best position.

Trajectory-Based Approaches
Thes approaches only consider one incumbent parameter set per iteration and move around the parameter space while balancing diversification and intensification. This way neighbourhoods can be searched relatively efficiently. Typical examples are simulated annealing (SA) and tabu search (TS). SA mimic the crystallisation of materials by randomly searching for new solution and accepting solutions that are worse than the current incumbent solutions with a decreasing probability over time. Thereby they first explore the solution space broadly before narrowing in on a promising neighbourhood. TS deterministically finds a best improving variation of parameters, while neglecting already explored attributes to avoid cycling on locations.

Hybrid Approaches
Hybrid approaches couple a meta-heuristic layer with a specialised solver that operates inside of a neighbourhood. These approaches still require a specific predictive model but utilise meta-heuristics to accelerate the search process.

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[76] Though it is often possible to adjust hyperparameters to improve the performance of a meta heuristic with respect to a specific problem instance.
[77] Usually referred to as fitness.
[78] Also sometimes referred to as evolutionary algorithms.

A1.4 Decision Selection Methods

Decision problems fundamentally refer to the selection of one alternative from the set of known available options. Each alternative may only fulfil the normative objectives of the DMC to a limited extend, thus a trade-off between objectives exists. To describe the preferences of a DMC with respect to a set of objectives, the concept of utility can be used. When the set of alternatives is explicitly defined multi-attribute decision making (MADM) methods are applicable, whereas for implicitly defined alternatives, multi-objective decision making (MODM) methods are applied (Hwang & Yoon, 1981, p. 3).

Utility Theory & Objective Structure

The utility of a decision describes the degree of satisfaction resulting from an alternative. A utility function $f^{(UTIL)}\colon \boldsymbol{r} \to V$ maps an outcome $\boldsymbol{r}$ to a utility value V. Such a function can only be explicitly determined if the DMC has a complete and transitive preference ranking for the set of possible outcomes $\boldsymbol{r} \in \boldsymbol{R}$. Three categories of utility functions can be distinguished: (i) extremisation, where $r_1 < r_2 \Rightarrow V(r_1) < V(r_2), \forall r_1, r_2 \in R$ or $r_1 < r_2 \Rightarrow V(r_1) > V(r_2), \forall r_1, r_2 \in R$, (i) approximation, where V increases with proximity to one or multiple distinct results, and (iii) satisfaction, where a requirement level of $\mathfrak{r}$ has to be reallised for V to be greater than 0. (Klein & Scholl, 2012, pp. 97–103)

In case of multiple objectives pursued in a decision, the relations between those objectives have to be considered. If the objectives o_1 and o_2 are entirely comlementary, i.e. $V_{o_1}(r_1) < V_{o_1}(r_2) \Rightarrow V_{o_2}(r_1) < V_{o_2}(r_2), \forall r_1, r_2 \in R$, a single objective can be chosen as a criterion. If the objectives are indifferent, i.e. the satisfaction of o_1 is entirely independent from the satisfaction of o_2, the problem can be decomposed into independent subproblems. If the objectives are however conflicting, which is the typicall case, a preference has to be defined between the objectives. With this preference a function $f^{(PREF)}\colon \boldsymbol{V}_O^{(PART)} \to V$ mapping the the vector of partial utilities $\boldsymbol{V}_O^{(PART)}$ of each objective $o \in O$ to the global utility V can be defined. (Klein & Scholl, 2012, pp. 104–116)

The definition of objectives and their relations is a crucial aspect of decision making. This definition encompasses, the generation of objectives and their structuring in an objective system. Objectives can be generated through the careful analysis of the problem situation, by investigating preliminary decision alternatives, or by derivation existing objective systems, like the normative objectives of the organisation. A structure of objectives can either be created top-down, by operationalising fundamental objectives into elementary ones or bottom-up, by grouping operational objectives until a shared set of superordinate objectives is reached. The resulting objective systems should be a *complete* representation of the decision situation, *operationalised* in the sense that the fulfilment of objectives is measurable, it should be *free of redundance*, i.e. objectives should be disjoint, *congruent with the organisation*, so that a practical subdivision into subproblems to be solved by different instances is possible, *simple and structured*, *free of conflict*, and *current*. (Klein & Scholl, 2012, pp. 129–136)

Multi-Attribute Decision Making

There are a number of ways to distinguish MADM methods. A common classification distinguishes MADM methods by the type of preference evaluation mechanism into value measurement, reference level, and outranking method. In the following methods of all tree classes are briefly introduced based on the more detailed description in (Bozorg-Haddad, & Loáiciga et al., 2021, p. 17ff.). Value measurement methods build a single score for each alternative. Those include weighed sum, weighed product, the analytic hierarchy process, and the analytic network process. Reference-level methods judge alternatives by their distance to a reference point. An example is the TOPSIS method. Outranking methods establish binary relations between alternatives to establish an overall ranking. Examples include ELECTRE and PROMETHEE.

Weighed Sum

The simplest but probably most used MADM method is *weighed sum*, where the utility V_α of an alternative α is described as

$$V_\alpha = \sum_{o \in O} w_o \frac{v_{\alpha,o} - v_o^{(L)}}{v_o^{(U)} - v_o^{(L)}} \qquad \text{Equation A 13}$$

where w_o is the weight[79] given to the objective o with $\sum_{o \in O} w_o = 1$, $v_{\alpha,o}$ is the performance rating of α on o, and $v_o^{(U)}$ and $v_o^{(L)}$ are the upper and lower bounds for performance on o[80]. The alternatives $\alpha \in \mathrm{A}$ are then ranked according to V_α.

Weighed Product

An alternative that penalises large variations in performance more is the similar *weighed product* method where the utility is defined as follows:

[79] Choosing weights is critical in most MADM methods. Weights can either be defined directly or using more involved methods like pairwise comparisons.

[80] The bounds can be defined explicitly or implicitly as $v_o^{(U)} = \max_{\alpha \in \mathrm{A}}(v_{\alpha,o})$ and $v_o^{(L)} = \min_{\alpha \in \mathrm{A}}(v_{\alpha,o})$.

$$V_\alpha = \prod_{i \in I} \left(\frac{v_{\alpha,i} - v_i^{(L)}}{v_i^{(U)} - v_i^{(L)}} \right)^{w_i} \quad \text{Equation A 14}$$

Analytic Hierarchy Process

Whereas the previous methods largely relegate the selection of objectives and there weighing to the intuitions of the DMC, the *analytic hierarchy process* (AHP) uses a more sophisticated process to determine both. In AHP criteria are structured from the overall objective at level 1 into n incresingly detailed levels. These levels are defined by the DMC ensuring, that all aspects of a decision are considered. The global weight w_o of an objective $o_1 \in O_k$ at level $k \in (2, n)$ is defined as

$$w_{o_1} = \sum_{o_2 \in O_{k-1}} w_{o_1,o_2} w_{o_2} \quad \text{Equation A 15}$$

where w_{o_1,o_2} denotes the relative weight of an objective o_1 for a superior objective o_2. To determine the relative weights, a pairwise comparison determining the relevance of each objective $o_1 \in O_k$ is performed for each $o_2 \in O_{k-1}$. In the pairwise comparison the relative importance ψ_{o_1,o_3,o_2} of o_1 compared to another objective $o_3 \in O_k$ is determined such that $\psi_{o_1,o_3,o_2} = \frac{1}{\psi_{o_3,o_1,o_2}}$ and $\psi_{o_1,o_1,o_2} = 1$[81]. The relative weight w_{o_1,o_2} is calculated as

$$w_{o_1,o_2} = \frac{\sum_{o_3 \in O_k} \psi_{o_1,o_3,o_2}}{\sum_{o_3 \in O_k} \sum_{o_4 \in O_k} \psi_{o_4,o_3,o_2}} \quad \text{Equation A 16}$$

To ensure consistency of the pairwise comparison, an eigenvalue-based consistency index is determined to check the assessments of the DMC and require an iteration if a consistency threshold is not met. Finally, the utility of an alternative can be determined using a pairwise comparison of the alternatives for each criterion of level n.

Analytic Network Process

The previously introduced AHP assumes the criteria on each of its levels are independent from one another. While this is a reasonable assumption in many decision situations, there may be cases where it does not hold. The more generalised form of AHP is the *analytic network process* (ANP), which forgoes this assumption.

In ANP, influences between each element and even looped influences can be considered. To this end, an influence matrix A with entries $a_{i,j}$ is constructed, where $a_{i,j}$ denotes the relative importance based on a pairwise comparison of element i vis-à-vis

[81] Though a nine-point scale is proposed by Saaty (2008), any arbitrary scale can be used.

element j. This step is repeated for all relations within or across clusters of interest. The elements $i, j \in N$ contain the alternatives, intermediate objectives, and the ultimate goal. From A the following relation can be used:

$$Aw = \lambda_{max} w \quad \textit{Equation A 17}$$

to derive the eigenvectors w using the largest eigenvalue λ_{max}. The eigenvectors of multiple pairwise comparisons can then be assembled to a super matrix W, which is column-normalised to W' with

$$W'_{i,j} = \frac{W_{i,j}}{\sum_{i \in N} W_{i,j}} \; \forall i, j \in N \quad \textit{Equation A 18}$$

This normalised super matrix is then iteratively stabilized to W^*:

$$W^* = \lim_{k \to \infty} (W')^k \quad \textit{Equation A 19}$$

In this stable super matrix, the column identity:

$$W^*_{i_1,j} = W^*_{i_2,j} \; \forall i_1, i_2, j \in N \quad \textit{Equation A 20}$$

Allows the utility U_j of an element j to be directly drawn as $U_j = W^*_{i,j} \; \forall i, j \in$. (Taherdoost & Madanchian, 2023, p. 16)

TOPSIS

The Technique for Order Preference by Similarity to Ideal Solution is a reference-level method that evaluates alternatives based on their similarity to an ideal solution, and by extension, the distance to the anti-ideal solution. The ideal and anti-ideal solutions are determined by combining the best and worst values in the entire alternative set[82]. The value V_i of an alternative i is then determined using the Euclidean distance of an alternative's values from the ideal and anti-ideal solutions S_i^+ and S_i^-:

$$V_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad \textit{Equation A 21}$$

The resulting Value V_i is between $(0, 1)$ with higher values indicating better solutions. This method is intuitive to interpret and relatively easy to compute for large sets of alternatives.

[82] In some cases, they may also be set from external references.

PROMETHEE II

The Preference Ranking Organization Method for Enrichment Evaluations is an outranking method that extends the simple pairwise comparison. It determines how much an alternative dominates others in the population I with size N_I and how much it is dominated as positive and negative outranking flows ϕ_i^+ and ϕ_i^-:

$$\phi_i^+ = \frac{1}{N_I - 1} \sum_{j \in I/\{i\}} v_{i,j} \quad \textit{Equation A 22}$$

$$\phi_i^- = \frac{1}{N_I - 1} \sum_{j \in I/\{i\}} v_{j,i} \quad \textit{Equation A 23}$$

Where $v_{i,j}$ denotes the pairwise preference degree between i and j. Different preference function can be chosen to adapt to attitudes towards difference. The net flow used for ranking is then determined as ϕ_i:

$$\phi_i = \phi_i^+ - \phi_i^- \quad \textit{Equation A 24}$$

ELECTRE

ELECTRE is a family of outranking methods that operates on iterative ranking procedures. It takes into account single poor criteria to block outranking of alternatives. It thereby avoids solutions that heavily compromise few criteria in favour of others. A detailed description is provided in…

Other MADM Approaches

A less common approach is the use of MADM methods as contributions to the parametrisation of a prescriptive model. This concept can be applied by giving a type of decision variable a desirability score based on qualitative assessment and integrating this score in the quantitative assessment as shown for example by Reich et al. (2019).

Multi-Objective Decision Making

MODM problems are characterised by more than one, typically conflicting objectives. The task of any MODM method is to determine a set of solutions that express the normative preferences of the DMC. A general MODM problem may be stated as follows (Deb, & Sindhya et al., 2017, pp. 146–147):

$$\begin{aligned} \min_{\boldsymbol{x}}/\max f_i(\boldsymbol{x}), &\quad i \in (1, N_I); \\ g_j(\boldsymbol{x}) \geq 0, &\quad j \in (1, N_J); \\ h_k(\boldsymbol{x}) = 0, &\quad k \in (1, N_K); \\ x_l^{(L)} \leq x_l \leq x_l^{(U)}, &\quad l \in (1, N_L) \end{aligned} \quad \textit{Equation A 25}$$

Where $\boldsymbol{x} = \left(x_1, x_2, \dots, x_{N_L}\right)^T$ is a solution vector, $x_l^{(L)}$ and $x_l^{(U)}$ are the lower and upper variable bounds constituting the decision variable space $\mathcal{D}$. In contrast to the previously introduced single objective decision making problems, the objective function $\boldsymbol{f}: \mathcal{F} \rightarrow \mathcal{Z} = \left(f_1(\boldsymbol{x}), f_2(\boldsymbol{x}), \dots, f_{N_I}(\boldsymbol{x})\right)^T$ maps the space of feasible solutions $\mathcal{F}$ to an N_I-dimensional objective space $\mathcal{Z}$. Within $\mathcal{Z}$ a set of *Pareto-optimal solutions* $\mathcal{O}$, also called *Pareto-optimal front*, may be identified containing all non-dominated solutions $\boldsymbol{x}^* \in \mathcal{O}$ such that (Azzouz, & Bechikh et al., 2017, p. 33; Ehrgott, 2005, p. 7):

$$\nexists \boldsymbol{x} \in \mathcal{F}: f_i(\boldsymbol{x}) \succ f_i(\boldsymbol{x}^*) \forall i \in (1, N_I) \qquad \textit{Equation A 26}$$

Where $\succ$ denotes pareto dominance. For the further steps it is important that an algorithm finds a set of solutions $\tilde{\mathcal{O}}$ that is (i) as close as possible to $\mathcal{O}$ and (ii) as diverse as possible (Deb, & Sindhya et al., 2017, p. 148). In many methods the *ideal objective vector* $\boldsymbol{z}^* = \left(z_1^*, z_2^*, \dots, z_{N_I}^*\right)^T \in \mathcal{Z}$ is used (Deb, & Sindhya et al., 2017, pp. 148–149; Ehrgott, 2005, p. 34), which is defined as:

$$z_i^* = \min_{\boldsymbol{x}} f_i(\boldsymbol{x}): \boldsymbol{x} \in \mathcal{S} \qquad \textit{Equation A 27}$$

In general, four types of approaches can be distinguished to solve MODM, based on their interaction with the DMC and their expression of preference: (i) no-preference approaches, (ii) a-priori approaches, (iii) a-posteriori approaches, and (iv) interactive approaches. *No-preference approaches* do not assume any specific preference between the different objectives. *A-priori approaches* require the DMC to specify their preference regarding the objectives before knowing the results, whereas *a-posteriori approaches* let the DMC chose solutions, thereby expressing their preference. The former requires the DMC to know what they value ahead of time, which can be challenging. The latter however require significantly more computational effort, as more potential solutions need to be provided. *Interactive approaches* bridge this gap by providing a sequence of interaction between the DMC and the decision-making method. (Deb, & Sindhya et al., 2017, pp. 157–158)

In the following, some of the most common MODM approaches are presented, many of which may be used in multiple interaction forms.

The *weighting method* collapses the MODM problem into a one-dimensional optimisation problem with (Ehrgott, 2005, p. 65):

$$\min_{x \in \mathcal{S}} \sum_{i \in (1,N_I)} w_i f_i(\boldsymbol{x}) \qquad \textit{Equation A 28}$$

where w_i denote the weights for each objective. This method is conductive to linear optimisation and may be used both a-priori and a-posteriori. The method is however unable to identify solutions in nonconvex regions of $\mathcal{O}$. (Deb, & Sindhya et al., 2017, pp. 159–160)

ϵ-constraint methods also collapse the MODM problem into a one-dimensional optimisation problem by transforming all but one objective functions into constraints using (Ehrgott, 2005, pp. 98–99)

$$\min_{x \in \mathcal{S}} f_j(\boldsymbol{x}) \; : \; f_i(\boldsymbol{x}) \preccurlyeq \epsilon_i \forall i \neq j \qquad \textit{Equation A 29}$$

This expression ensures linearity but is more computationally expensive than the weighing method due to the additional constraints. The method is able to find solutions in nonconvex regions of $\mathcal{O}$, but the method is very sensitive to the choice of j and ϵ_i. The method can be used both a-priori and a-posteriori. (Deb, & Sindhya et al., 2017, pp. 160–161)

Lexicographic ordering is a sequential procedure by which the objectives are ranked by priority a-priori. Then the problem is solved sequentially for each objective j such that

$$\min_{x \in \mathcal{S}} f_j(\boldsymbol{x}) \; : \; f_i(\boldsymbol{x}) \leq \min_{x \in \mathcal{S}} f_i(\boldsymbol{x}) - \delta_i \forall i \succ j \qquad \textit{Equation A 30}$$

Here δ_i denotes the allowed finite slip between the the optimal solution for f_i and the updated solution. This method consists of multiple successive linear objectives. The method is relatively accessible to DMC as a priorisation are easier to express then specific weights. The method is also more computationally expensive then the weighting method due to the additional constraints. For small δ_i the method can also terminate very quickly.

Metric-based methods, sometimes referred to as point-distance methods or compromise programming, minimise the weighed distance to an aspirational point $\bar{\boldsymbol{z}} \in \mathcal{Z}$ often with $\bar{\boldsymbol{z}} = \boldsymbol{z}^*$ (Deb, & Sindhya et al., 2017, p. 162):

$$\min_{x \in \mathcal{S}} \left(\sum_{i \in (1,N_I)} w_i |f_i(\boldsymbol{x}) - \bar{z}_i|^p \right)^{\frac{1}{p}} \qquad \textit{Equation A 31}$$

where $p \in [1, \infty]$ is an Euklidian metric. These methods can also be used a-priori or a-posteriori. They are generally computationally expensive, as they are only linear for $p =$

1. The use of a reference point chosen by the DMC has generally been found to be as relatively intuitive form of a-priori MODM (Larichev, 1992, p. 131).

Goal programming uses an a-priori defined aspirational point $\bar{\boldsymbol{z}} \in \mathcal{Z}$ and minimise the weighed positive distances δ_i^+, reducing the MODM problem to a linear problem with additional decision variables and constraints. (Deb, & Sindhya et al., 2017, pp. 172–173)

$$\min_{\boldsymbol{x},\delta^+} \sum_{i\in(1,N_I)} w_i \delta_i^+ : \\ f_i(\boldsymbol{x}) - \delta_i^+ \leq \bar{z}_i \forall i \in (1, N_I); \\ \delta_i^+ \geq 0 \forall i \in (1, N_I), \boldsymbol{x} \in \mathcal{S}$$

Equation A 32

Evolutionary multi-objective optimisation (EMO) are meta-heuristic methods for MODM. They generally seek to find a set of solutions that resemble $\mathcal{O}$ as well as possible and allow DMC to choose their preferred solution a-posteriori (Deb, & Sindhya et al., 2017, p. 165). They are generally more computationally expensive and cannot guarantee optimal solutions. Some approaches reach relatively high efficiency by sampling solutions generated through different decompositions of the MODM problem into a MILP (Deb, & Sindhya et al., 2017, p. 166). An overview of existing EMO approaches for dynamic problems is provided by Azzouz et al. (2017).

Interactive methods describe an iterative procedure, where DMC are shown a set of information regarding the problem, the DMC state an initial preference, which is translated into a set of alternate solutions. Depending on the satisfaction of the DMC, the process is repeated. The method balances computational effort and ability for the DMC to express their preference but require a prolonged decision time and multiple interactions with the DMC. A more detailed description of different interactive methods is provided by Deb et al. (2017, pp. 173–178).

Sensitivity Analysis

Sensitivity analysis is used to analyse the contribution of different parameters to a solution. This can help to determine the robustness of a solution by varying uncertain inputs or to find parameters of particular interest. In general, different sensitivity analysis techniques seek to find s_k for a predictive or prescriptive model $f(\boldsymbol{p})$ where $\boldsymbol{p}$ is the parameter vector with values p_k:

$$s_k = \frac{\partial f}{\partial p_k} \frac{p_k}{f}$$

Equation A 33

Higher values of s_k indicate a higher sensitivity to the parameter. This may of course also be performed for multidimensional functions $\boldsymbol{f}$.

Post-Optimality Analysis

Post-optimality analysis (POA) describes techniques to further analyse results obtained from prescriptive models and deduce insights on the costs[83] of constraints. This can be done using the dual values of constraints. This allows for a deeper understanding of decisions. For example, decision-makers may choose to ignore actions that only marginally improve outcomes but come with other costs that are not accounted for.

Multi-Stakeholder Decision Making Methods

When multiple stakeholders are involved in decisions it may be necessary to adapt the decision-making methods accordingly. To this end, group variations of various MADM methods exist, which aggregates weights and scores across stakeholders. Alternatively, the resulting rankings can be used as voting ballots. Furthermore, bargaining methods that use Nash products and privately determined utilities of every stakeholder can be used to determine the most suitable and fair compromises.

A1.5 Scenario Generating Methods

Scenario generating methods aim to describe the uncertain development of the system environment[84] across the time horizon (Mietzner & Reger, 2005, pp. 223–225). For probabilistic predictive and prescriptive models and models with internal randomness, this uncertainty can be expressed as probability density functions for different environmental parameters. However, for most models considered here, a discrete set of scenarios should be developed, which may be used to evaluate the chosen configuration. Depending on the availability of data to describe different probabilities and dependencies, both manual and automated methods are applicable.

Scenario Techniques

Scenario technique describes a group of methods to design consistent future scenarios, usually involving multiple people. The techniques make sure, that a wide array of influences is considered and then seek to align them in consistent future scenarios. Different procedural models for scenario development exist. Börjeson et al. (2006, pp. 730–735)

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[83] Here, costs referrers to not realised potential of a particular objective due to a constraint.

[84] The term scenario is not strictly defined and, in many cases, used to describe both potential external developments and alternative actions and their consequences. In the interest of clarity, this work only uses the term scenario when referencing external scenarios.

propose a three step procedure of scenario generation, integration, and consistency. In each phase, different methods may be applied. An overview of additional scenario techniques is provided by Bishop et al. (2007). They distinguish eight categories of techniques, which differ significantly in terms of their starting point, their process, and their product. (i) *Judgement techniques* focus explicitly on supporting human creativity, (ii) *baseline scenarios* extrapolate one most likely development path from current trends, (iii) *fixed scenario elaboration* are exploring and detailing predetermined scenarios, (iv) *event sequences* model developments as a diverging tree of possible future events and their implications, (v) *back casting* develops scenarios from predetermined end-points to avoid biases of current trends, (vi) *dimensions of uncertainty* approaches systematically analyse different sources of uncertainty to infer resulting scenarios, (vii) *cross-impact analysis* examines the interrelationships between multiple future events and forecast results using Monte-Carlo simulation (MCS), and (viii) *modelling techniques* include stochastic uncertainty in models for future development (Bishop, & Hines et al., 2007, pp. 11–17). According to Börjeson et al. (2006, pp. 725–730) resulting scenarios can be distinguished in terms of their implication for the users into predictive (i) forecasts and (ii) what-if scenarios, explorative (iii) external and (iv) strategic scenarios, and normative (v) preserving or (vi) transforming scenarios. In this work, the focus is placed on external scenarios, which only consider the developments of the environment outside the user's control.

Scenario techniques require significant effort but lead to scenarios that are intelligible. As the scenario generation is mostly manual, only limited data is necessary even if multiple different domains and their interplay such as geopolitics, economic, societal, and environmental developments, and market trends are considered. The methods are however susceptible to biases of the participants and likelihood estimations for different scenarios are very rough. Furthermore, significant translation effort is required to describe the implication of any given scenario with respect to a predictive model.

Forecasting Methods

Forecasting methods use historical data, usually in the form of a timeseries, to infer predicted developments and distributions of likely developments (Petropoulos, & Apiletti et al., 2022, pp. 710–711). A wide array of different quantitative methods to create forecasts exist, which can be applied depending on the available data. One of the most common categories of approaches are statistical and econometric models, such as exponential smoothing, time-series regression, autoregressive integrated moving average

(ARIMA), state space models, and others (Petropoulos, & Apiletti et al., 2022, pp. 712–731).While these methods usually only provide a single estimate, Bayesian forecasting is probabilistic by nature and describes the probability density function of future states while considering uncertainties regarding the considered inputs. In a simple Bayesian forecast the probability density $p(y_{t+1}|\boldsymbol{y})$ of a future state y_{t+1} of a variable at time $t+1$ given historical data $\boldsymbol{y}$ is defined as (Petropoulos, & Apiletti et al., 2022, p. 731):

$$p(y_{t+1}|\boldsymbol{y}) = \int p(y_{t+1}|u,\boldsymbol{y})\mathfrak{p}(u|\boldsymbol{y})du \qquad \textit{Equation A 34}$$

where u denotes the model unknowns. When multiple scenarios should be considered, Bayesian forecasting or methods that include some representation of the probability density function (PDF) of variables are desirable. Knowledge of the PDF may also be used to specifically consider unlikely scenarios to improve resilience (Nassehi, & Colledani et al., 2022, p. 678).

Forecasting methods are particularly potent when reliable data are available and describe future developments well. The generation of forecasts that form the foundation for the decision-making process can be automated using these methods.

Monte-Carlo Simulation

Monte-Carlo Simulation (MCS) describes a process by which samples are drawn randomly from PDFs. Each random sample can then be treated as a deterministic parameter set for a function f. Based on the strong law of large numbers, the distribution of results approaches the PDFs for sufficiently large samples (Rubinstein & Kroese, 2007, p. 15):

$$\mathbb{P}\left(\lim_{N\to\infty}\left(\frac{1}{N}\sum_{i\in N}(f(X_i)) = \mu\right)\right) = 1 \qquad \textit{Equation A 35}$$

Where $\mathbb{P}(x)$ denotes the probability of x and the expected value of f is $\mathbb{E}[f(X)] = \mu$. To choose sufficiently large N, the following estimator can be used to determine the mean value of a distribution:

$$N \geq \frac{\varsigma^2 z^2}{\epsilon^2} \qquad \textit{Equation A 36}$$

where ς is the standard deviation of the random distribution, $\epsilon = \mu - \delta$ is the allowed deviation from the actual mean μ, and z is the corresponding z-score denoting the share of the distribution inside ϵ.

Receptor Model

As quantitative models focus on a particular system, uncertainty regarding future development of its environment e is not always trivial to integrate into a model m. For example, a scenario may describe a stunted global economy, but how this is related to the specific order volumes parametrising an investment planning model is not clear. Receptor models bridge this gap by providing a mapping function $\boldsymbol{f}^{(RCP)}(\boldsymbol{y}_e(\theta)) = \boldsymbol{p}_m^{(ENV)}$, where $\boldsymbol{y}_e(\theta)$ describes the states of the environment throughout time θ and $\boldsymbol{p}_m^{(ENV)}$ the models parameters determined by its environment[85]. Receptor models can be used either to map specific scenarios to model parameters or to specify the distribution of parameters in stochastic models based on multiple scenarios. (Cisek, & Habicht et al., 2002, p. 442; Treber, 2020, p. 63ff.)

A1.6 Meta Models

Meta models, also referred to as surrogate models provide a way to circumvent situations where the calculation of the respective predictive or prescriptive model is to computationally costly, or a particular characteristic of the model is desirable. Generally meta models are fitted to the results of an original model using base points where model results are calculated. They then represent the original model function $f(\boldsymbol{x})$ with an approximation:

$$\hat{y} \approx f(\boldsymbol{x}) \qquad \textit{Equation A 37}$$

Depending on the characteristics of the meta model and the original model different distributions of base points and different sampling and training methods are favourable. Meta models can be particularly useful, when decision times are too short for the original models and the relevant parameter space may be adequately represented with a simplified model. In the following, a selection of relevant meta models is presented. In general, classical regression models and neural networks can be distinguished.

Gaussian Process Regression

Predicts the value of the model using a trend function $f^{(GPR)}(\boldsymbol{\beta}, \boldsymbol{x})$ and the realisation of a stationary normally distributed Gauss process $Z(\boldsymbol{x})$.

$$\hat{y} = f^{(GPR)}(\boldsymbol{\beta}, \boldsymbol{x}) + Z(\boldsymbol{x}) \qquad \textit{Equation A 38}$$

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[85] Receptor models assume that the relation between the environment and the system is unilateral.

this results in a smooth infinitely differentiable function. Gaussian Process Regression or Kriging is particularly useful if the number of sampling points is relatively low. (Law, 2015, p. 676)

Response Surface Methodology
A regression method that approximates the model with a polynomial, usually of second order:

$$\hat{y} = \beta_0 + \sum_i \left(\beta_i x_i + \beta_{i,i} x_i^2 + \sum_{j<i} \left(\beta_{i,j} x_i x_j \right) \right) \quad \textit{Equation A 39}$$

where x_i are the components of $\boldsymbol{x}$ and the parameters β_0, β_i, and $\beta_{i,j}$ are determined using least squares fitting. This method is suited if the response surface is smooth and approximately quadratic. (Myers, & Montgomery et al., 2016, p. 4)

Multivariate Adaptive Regression Splines
A regression method that approximates the function with a piece-wise linear model:

$$\hat{y} = \beta_0 + \sum_i \left(\beta_i B_i(\boldsymbol{x}) \right) \quad \textit{Equation A 40}$$

where $B_i(\boldsymbol{x})$ are linear hinge functions. This type of meta model is most suitable when the function approximates linearity in specific areas. It is relatively well interpretable and can be used as a MILP. (Siebertz, & van Bebber et al., 2017, 254f)

Feed-Forward Neural Networks
Represents the model by a set of layers $l \in L$ containing “neurons” with typically non-linear activation functions σ based on weighed inputs from the previous layers.

$$\boldsymbol{a}_0 = \boldsymbol{x} \quad \textit{Equation A 41}$$

$$\boldsymbol{a}_l = \sigma(\boldsymbol{W}_l \boldsymbol{a}_{l-1} + \boldsymbol{b}_l) \quad \textit{Equation A 42}$$

$$\hat{y} = a_L \quad \textit{Equation A 43}$$

where $\boldsymbol{W}_l$ denotes the weight matrix between $l - 1$ and l, and $\boldsymbol{b}_l$ are activation biases. These networks can generally learn using back propagation. They require very large training sets but can adapt to a broad range of functions. (Sammut & Webb, 2011, p. 988)

A1.7 Method Application in Academic Literature & Industrial Practice

The methods illustrated above are applied extensively for PNC and related problems by academics as is apparent in literature reviews (Govindan, & Fattahi et al., 2017; Melo, & Nickel et al., 2009; Peidro, & Mula et al., 2009; Volling, & Matzke et al., 2013). Evidently, academic literature using quantitative decision support methods for a supply chain perspective according to Rudberg and Olhager (2003, pp. 29–30) is far more prevalent than literature focusing on the manufacturing network perspective. Nevertheless, valuable insights can be drawn from these reviews.

The most commonly applied methods for the investigated problems are optimisation approaches, of which about half are using a problem specific solution approach, while the other half uses commercial solvers. Costs remain the most important objective used by such approaches, though other objectives, e.g. environmental impact and delivery time, are also considered. Approaches typically only consider a limited selection of complexity inducing model design options, such as multi-objectives, multi-periods, multi-products, multi-echelon, multi-organisation, stochasticity, etc. It is likely that approaches applied in industrial practice feature even fewer of these design options.

A2 Decision Support System Resources

Table A 1: Symbols Used in Appendix A2

Symbol	Description	Unit
$\emptyset$	Empty set	
$\Rrightarrow$	Hierarchically superior	
$\rightleftharpoons$	Interlocked	
$\rightharpoonup$	Semi-locked	
$\Rightarrow$	Dependent	
$\rightarrow$	Semi-dependent	
$\nRightarrow$	Independent	
$\Leftrightarrow$	Conflicting	
$\looparrowleft$	Semi-conflicting	
$\rightleftarrows$	Complimenting	
$\nLeftrightarrow$	Non-conflicting	
$\rightsquigarrow$	Refining	
$\curvearrowright$	Rendering	
$\twoheadrightarrow$	Optimising	
$\leadsto$	Reevaluating	
m	Model	
p	Enforcement strength of proximity constraint	
$X_m^{(FIX)}$	Set of fixed decision variables in model m	
$X_\pi^{(FIX)}$	Set of fixed decision variables in decision process π	
$X_m^{(INC)}$	Set of inconsequential decision variables in model m	
$X_\pi^{(INC)}$	Set of inconsequential decision variables in decision process π	
$X_m^{(INC,PDC)}$	Set of predictively defined inconsequential decision variables in model m	
$X_m^{(INC,PSC)}$	Set of prescriptively defined inconsequential decision variables in model m	
$X_m^{(PDC)}$	Set of predictively defined decision variables in model m	

Symbol	Description	Unit
$X_m^{(PSC)}$	Set of prescriptively defined decision variables in model m	
$X_m^{(SUB)}$	Set of subject decision variables in model m	
$X_\pi^{(SUB)}$	Set of subject decision variables in decision process π	
$X_m^{(SUB,PDC)}$	Set of predictively defined subject decision variables in model m	
$X_m^{(SUB,PSC)}$	Set of prescriptively defined subject decision variables in model m	
$\boldsymbol{x}$	Input parameter vector	
$\boldsymbol{y}$	Response vector	

A2.1 Decision Situation Characteristics & Relation to PNC Properties

In the following, the decision situation characteristics are described in detail, and their relation to PNC properties is specified. This characterisation may be used to assess the decision situation characteristics present in a particular DSS development instance. Provides an overview of the characteristics.

Table A 2: Decision Situation Characteristics & Relevant PNC Properties

Decision Situation Characteristic		Description	Focal Company	Objectives	Domains	PNC Elements	External Influences	Process Char-acteristics
DC 01	System Linearity	Degree to which linear equations can adequately describe the relevant system behaviour.	x	x	x	x	x	
DC 02	Number of Decision Variables	Number of distinct variables to be determined in the decision.	x	x	x	x		
DC 03	System Expertise	System expertise of the DMC, specifically central DSS users.	x		x			x
DC 04	Uncertainty	Degree to which the outcome of the system is impacted by and sensitive to uncertain developments.	x	x		x	x	
DC 05	Decision Frequency	Frequency with which similar decisions are made.	x			x		x
DC 06	Decision Routine	Degree to which the decision is standardised, the process is predefined, and the necessary inputs are known.	x			x		x
DC 07	Development Capabilities	Capabilities of the organisation to develop DSS solutions.	x					x
DC 08	Perspective Diver-sity	Degree to which multiple distinct interests with different over-arching objectives have to be satisfied in the decision.	x	x	x			x
DC 09	Achievable Accuracy	Grade of accuracy that is achievable with the available data.	(x)	x		x	x	
DC 10	Objective Quantifiability	Degree to which the pursued objectives can be quantified.		x				x
DC 11	Data Acquisition Intensity	Amount of data necessary for the decision.	(x)	x	x	x	x	

DC 12	Time Horizon	Length of time taken into consideration in the decision.	(x)		x	x		
DC 13	Decision Time	Available time to make the decision.	(x)			x		x
DC 14	Computing Capabilities	Available computational capabilities.	(x)					x
DC 15	Desired Explainability	Degree to which the decision needs to be understandable by and explained to decision makers.	(x)					x
DC 16	Model Expertise	Amount of model knowledge and understanding of the DMC.	(x)					x

The descriptions in the following sections are structured as follows: (i) general description of the characteristic and important influences, (ii) description of the influences, and (iii) description of the value range.

DC01: System Linearity

The system linearity describes the degree to which the behaviour of the system under consideration is described accurately by linear equations with continuous or discrete variables within the validity range defined by the desired application and with respect to the considered objectives. The accuracy is viewed in relation to the accuracy requirements. The linearity is affected by several PNC properties:

- Focal Company: Depending on the boundaries of the system of consideration, the characteristics of the focal company affect the linearity. For example, material prices can be a non-linear function of demand volumes in certain markets and for corresponding company sizes. Average set-up times can be a non-linear function of the production order variance if for example the number of distinct set-ups is of the same magnitude as the number of available resources. These non-linear characteristics are specific and evade a complete description. These influences on linearity largely moderate the effects of other influences like considered objectives, domains, PNC Elements, and external influences.
- Objectives: Some objectives like costs or greenhouse gas emissions behave largely linearly with regard to produced volumes and used resources, whereas others, like delivery reliability or flexibility are non-linear by nature.
- Domains: Depending on the objectives the linearity is also affected by the considered domains. For example, the relation between production characteristics and sales volume is largely non-linear.
- PNC Elements: Depending on the considered PNC elements and their change modes, non-linearities can occur. For example, the space demand in a production site a relation to the required capacity is not linear, particularly if the geometric limitations of buildings and production resources are considered.

- External Influences: The presence and strength of external influences may cause non-linear behaviour. For example, incomplete employee training may make productivity dependent on changes in the number of staff, thus making the relation between staff and capacity non-linear.

Range:

- Very low (1): The relevant behaviour of the system is highly non-linear, adequate linearisation techniques are not known.
- Very high (6): The relevant behaviour of the system is entirely described by linear equations, without the need to approximate or linearise aspects.

DC02: Number of Decision Variables

The number of distinct decision variables in a decision which are part of the decision subject set or the necessary inconsequential set. For example, a resource investment decision may require a decision on the allocation of production volumes to resources. The number of necessary variables is a characteristic of the decision situation. A specific model may introduce additional support decision variables necessary to realise a linear formulation of a boundary condition or objectives. These are not characteristics of the decision situation. This number of decision variables is affected by the following PNC properties:

- Focal Company: The size of the company, the heterogeneity of its production program, processes and resources and other aspects affect the number of variables to consider in any given process.
- Domains: The number and type of domains considered also affects the number of decision variables. For example, the addition of outbound logistics in capacity planning may lead to an addition of a large number of variables.
- PNC Elements: The considered PNC elements inherently influence the decision variables. Typically, there are more “smaller” PNC elements like tools and resources and fewer “large” elements like production sites. Thus, including these “smaller” elements with shorter change times can drastically increase the number of decision variables for the same size.

Range:

- Very low (1): Very low number of decision variables, enabling full enumeration and comprehension of all options by decision makers. (~10)

- Very high (6): Very large number of decision variables incomprehensible for decision makers and challenging to solve even for efficient linear models. (currently ~10^6)

DC03: System Expertise

The expertise the DMC and specifically parts of the DMC directly using the DSS have regarding the properties and dynamic behaviour of the system. This concerns the behaviour of the system in its entirety even if multiple domains are involved.

- Focal Company: In larger companies, the considered systems can be larger and harder to understand. Decision processes are also likely to be portioned into smaller parts, as more specialisation is possible. This may lead to less comprehensive system understanding. The degree to which a company records information about system properties and behaviour may also differ. Lastly, the experience and training of DMC members may differ.
- Domains: The number of involved domains may decrease understanding of any specific member while increasing the expertise concerning the behaviour of the production system as a whole.
- Process characteristics: Longer decision processes can allow for a more comprehensive understanding of the system as more expertise may be drafted. More frequent decisions may allow the DMC to be better trained on the system behaviour.

Range:

- Very low (1): The knowledge regarding the behaviour of the system is low and fractured across the DMC. Particularly DSS users do not have any experience of the system and no records on it are available.
- Very high (6): The behaviour of the system is very well understood even in uncommon conditions. The experience and knowledge are homogenously high and comprehensive throughout the whole DMC.

DC04: Uncertainty

The degree to which the system, and specifically the decision in question is shaped by influences which are not known to the DMC. This includes uncertainty regarding the system behaviour beyond missing expertise, but due to developments which cannot be entirely predicted. It also includes external uncertainty:

- Focal Company: The regions and markets the company is active in, the fragility of the production system, the reliance on suppliers and the size of the company all affects the degree to which uncertainties are relevant.
- PNC Elements: Elements with long change modes and higher investments are usually more impacted by uncertainty, as longer time horizons are more difficult to predict, and higher investments create a higher overall risk.
- External Influences: Higher influences of the company environment can lead to a higher overall level of uncertainty, as the development of complex environments is difficult to predict.

Range:

- Very low (1): The decision is entirely deterministic. The behaviour of the system and the external influences are entirely known, and no unforeseen influences are conceivable.
- Very high (6): The behaviour of the system is largely dependent on the development of both known and unknown unknowns. Any decision may only be taken with low confidence.

DC05: Decision Frequency

The frequency with which comparable decisions are made within the company. Comparable decisions follow the same rules, have a comparable system behaviour, and decide on the same type of decision variables. This frequency is mainly influenced by the focal company, the PNC elements, and the process characteristics:

- Focal Company: Larger companies face similar decisions more often, as they consist of more subdivided systems. More process-oriented companies can also make decisions more frequently or regularly.
- PNC Elements: Elements with shorter change times are typically reconsidered more frequently.
- Process characteristics: The degree to which the process is standardised and regularly executed or executed based on changes to the system may lead to higher frequency.

Range:

- Very low (1): The decision is very rare and only occurs once every five to ten years.

- Very high (6): The decisions are made regularly, for example every one to two months and across a broad range of different subsystems in the company.

DC06: Decision Routine

The degree to which decisions are made following a predetermined procedure, decision criteria are defined and followed, and inputs to the decision are known and current. This reflects the actual lived reality of the processes in practice, not the aspiration the company would like. This routine can be affected by several aspects:

- Focal Company: The degree of process orientation and the specification of processes can vary from company to company and even within companies themselves. Larger companies tend to standardise shorter term decision more, as they occur more frequently.
- PNC Elements: Decisions on shorter term elements tend to be more standardisable, as quantitative objectives are more important, and uncertainty plays a less important role.
- Process characteristics: The specific process organisation and assignment of responsibilities shapes standardisation and routine.

Range:

- Very low (1): The decision situation is unknown, important influences, the expected behaviour of the system, and decision criteria are not known.
- Very high (6): The decision situation is fully standardised, every step and responsibility are predetermined, and criteria and their use are defined.

DC07: Development Capabilities

The ability of the company to develop or insource advanced DSS. This includes expertise on the availability of data, development capabilities for relevant models and interfaces, availability of users willing to test novel solutions and investment budget and purchasing expertise. This characteristic is primarily shaped by the focal company and process characteristics:

- Focal Company: The development capabilities are shaped by the company. Larger companies tend to have more development capabilities and available investment budgets as well as a broader user base. The digital maturity of a company influences how experienced and well equipped the company is for development efforts overall.

- Process characteristics: Depending on the process and involved stakeholders the availability of budgets and the ability of users for developments may differ.

Range:

- Very low (1): The company has no own development capabilities, the users are not available for improvements, and no investment budgets are available.
- Very high (6): The company is experienced in developing DSS both on its own and in collaboration with external partners and users of the DSS in question are available for improvement projects.

DC08: Perspective Diversity

Degree to which the decision has to satisfy several different interests and perspectives in the company. This may involve competing objectives in terms of results but also interests of distinct functions and subsystems within the company, which are involved in the decision. This is mainly shaped by the focal company, objectives, domains, and process characteristics:

- Focal Company: The size of the company and the centralisation of decision making may influence the diversity of perspectives to be considered in a decision. Furthermore, the degree to which product or market-based divisions are interconnected affects the diversity of decisions.
- Objectives: The depending on the chosen objectives and their relation, the perspective diversity increases.
- Domains: More chosen domains increase perspective diversity.
- Process characteristics: The way a process is defined, and involvement of stakeholders is included shapes the diversity of perspectives.

Range:

- Very low (1): The decisions are made by a single function in a company and affect only a single well delimitable subsystem of the company is involved. The decision is made based on a single objective.
- Very high (6): The decision effects and relies on multiple distinct company functions and divisions. Multiple competing objectives and interest have to be considered and weighed against each other.

DC09: Achievable Accuracy

The accuracy of decision making that is theoretically possible, based on all available data concerning the system and its environment. This evaluates the quality of data available against the sensitivity of decisions for this type of data. It is influenced by the company, the objectives, relevant PNC elements, and external influences:

- Focal Company: The digital maturity of the company shapes its ability to capture accurate data on the system and its environment.
- Objectives: Some objectives lend themselves more to be accurately described with data, such as utilisation, while others like complexity reduction are difficult to capture in data.
- PNC Elements: Some PNC elements, typically those that change regularly tend to be more accurately captured in data.
- External Influences: External influences are usually more difficult to capture than own resources or other system characteristics. Furthermore, external influences differ in terms of the availability of adequate data sources. Thus, the strength and type of influences shapes the accuracy that is realistically achievable.

Range:

- Very low (1): Even when all available data is considered, the decision quality is likely poor, as the data quality is low and the decision is very sensitive to the data.
- Very high (6): The achievable decision quality is nearly perfect as all necessary data is available and of very good quality.

DC10: Objective Quantifiability

The degree to which the relevant objectives of the decision can be captured in a quantitative form that accurately reflects the trade-offs in the decision. It is assumed that the data is available and accurate. This is mainly affected by the chosen objectives and to an extent by the chosen process:

- Objectives: The pursued objectives can differ significantly in regard to the ability to capture them in data. Whereas monetary objectives are usually quantifiable, objectives such as social responsibility are very challenging to put into comparison.

- Process Characteristics: Even in cases where a quantification is difficult, the decision process can be designed to amend this using for example MADM techniques. This is usually easier if more decision time is available.

Range:

- Very low (1): The pursued objectives are hardly quantifiable and thus alternatives cannot be objectively compared. The decision relies almost entirely on decision maker instincts and non-specified preferences.
- Very high (6): The objectives can be completely captured in quantitative forms, and all alternatives are completely comparable.

DC11: Data Acquisition Intensity

The amount of data necessary for a decision, specifically considering how difficult it is to obtain all the necessary data. This intensity increases with the number of data sources that have to be accessed. This is influenced by the company characteristics, domains, PNC elements, and external influences:

- Focal Company: The digital maturity of a company affects how well different IS are connected across functions. The size of the company, the heterogeneity of products and splits of products and resources also increase the necessity to access multiple sources.
- Domains: The more distinct domains are involved in decisions, the higher the number of relevant sources.
- PNC Elements: More types of elements may lead to more diverse data demands. Furthermore, more long-term elements may also be characterised across a broader range of data sources.
- External Influences: More external influences can increase the data demands of the decision.

Range:

- Very low (1): The decisions can be made based upon data from a single source that is readily available and familiar to the users.
- Very high (6): The decision requires information from several distinct data source corresponding to different functions and divisions. The data is not structured in compatible formats and must be adapted accordingly.

DC12: Time Horizon

The timeframe a decision is relevant for. The consequences of a decision should be realised within the timeframe. This characteristic is affected primarily by the company characteristics, considered domains, and PNC elements:

- Focal Company: The degree to which high investment resources play a role in production and the overall speed of change characterised by lead times and product lifecycles affects the length of the time horizon.
- Domains: Including more long-term oriented domains like product development can increase the time horizon.
- PNC Elements: The change times of PNC elements determine the necessary time horizons that must be considered in a decision to evaluate any changes to them.
- External Influences: If long-term shifts in external influences are present, the time horizons must be adapted to reflect them.

Range:

- Very low (1): Very short-term configuration decisions in highly volatile systems of a few weeks.
- Very high (6): Extremely long-time horizons of more than a decade.

DC13: Decision Time

The time available to make a decision from the time the decision demand is known to the commitment to the result of the decision process. This is affected by the PNC elements, external influences, and process characteristics:

- PNC Elements: Short-term elements are usually present in high numbers and frequently require small adaptions. Decisions focused on them usually have less time available before a decision needs to be made.
- External Influences: External influences with high volatility and short effect times require quick adaptions, limiting the available decision time.
- Process Characteristics: Depending on the specific process in place to make a decision, the DMC can be given more or less time.

Range:

- Very low (1): Very short decision times of a few minutes.
- Very high (6): Very long decision times of multiple months up to a year.

DC14: Computing Capabilities

Computing capabilities the company has available to use in DSS. This may involve access to cloud computing and availability of general problem solvers. This is influenced by the company characteristics and process characteristics:

- Focal Company: Larger companies and companies with high maturity typically have a better availability of tools to compute solutions.
- Process Characteristics: Depending on the involved functions in the DMC, different computing capabilities may be granted.

Range:

- Very low (1): For the decision only open-source solutions run on office hardware are available.
- Very high (6): For the decision, scalable cloud computing capabilities and the best commercially available solvers and models can be used.

DC15: Desired Explainability

The degree to which a decision must be explained to parts of the DMC. This includes a specification of the assumptions, an explanation of the predicted system behaviour, causalities between the effects of different alternatives and the validity range of the decisions. This is primarily affected by company characteristics, domains, and process characteristics:

- Focal Company: The familiarity of the DMC with the decision may be affected by company size and the centrality with which decisions are typically made.
- Domains: The inclusion of additional domains with limited understanding of each other may necessitate a higher level of desired explainability.
- Process Characteristics: The importance of a decision may increase the level of desired explainability. Also, explainability may be specifically called for in decision process descriptions.

Range:

- Very low (1): The decision does not need to be explainable, if due process can be proven.
- Very high (6): The decision, its assumptions, predictions, consequences, and counterfactuals need to be explained comprehensively, such that multiple distinct perspectives may understand it.

DC16: Model Expertise

The expertise of the DMC regarding relevant modelling techniques. Here the parts of the DMC directly interacting with the DSS play the most important role, but expertise of other parts, especially such with final decision-making authority are also considered. This is influenced by the focal company and process characteristics:

- Focal Company: The digital maturity of the company may influence the familiarity of decision-makers with advanced modelling techniques.
- Process Characteristics: The set of DMC members involved and their integration into the process may shape the model expertise the DMC can bring to bear.

Range:

- Very low (1): The DMC has very little expertise regarding complex modelling techniques and cannot verify how a model would arrive at any conclusion.
- Very high (6): All relevant parts of the DMC have a high level of expertise on relevant models and can assess how and why a model would arrive at which conclusions and how models need to be set up to arrive at the most desirable results.

A2.2 Focal Company Characteristics

In the following the characteristics of focal companies (FC) and mechanisms to influence decision situation characteristics are introduced. These mechanisms are not tested empirically, and the strength of the effects may depend on several contributing factors. Instead, they may be used as a point of reference when assessing the decision situation characteristics. For each FC, a set of possible metrics used to assess them is provided, as well as a discussion of those metrics. An overview of the characteristics is given in Table A 3.

Table A 3: Focal Company Characteristics Relevant for DSS Design

Characteristic		Description	Impacted Decision Situation Characteristics
FC01	Organisation Size	Size of the organisation in terms of turnover, employees, & sites.	DC02, DC05, DC06, DC07, DC11, DC14, DC15
FC02	Decision Centrality	Degree to which relevant decisions are centralised in the company	DC01, DC02, DC03, DC05, DC06, DC07, DC08, DC15
FC03	Market Relation	Point of product creation process orders are introduced at	DC01, DC04, DC08
FC04	Resource Share	Share of resource cost in production costs	DC02, DC04, DC12
FC05	Product Heterogeneity	Degree to which products of the organisation differ from each other	DC02, DC08, DC11

FC06	Production Lead Time	Time between the start of production and finalisation of a product	DC04, DC12
FC07	Product Stability	Time a product type is sold in the market without change	DC04, DC05, DC12
FC08	Vertical Integration	Share of value creation performed within the company	DC01, DC03, DC04, DC08, DC11
FC09	Production Volume	Number of products produced	DC01, DC02, DC11
FC10	Production Technology Stability	Degree to which production technology remains stable across generations	DC01, DC02, DC03, DC04, DC05, DC08, DC11,
FC11	Commoditisation	Degree to which sales are determined by price	DC01, DC08
FC12	Production Splits	Split of production across sites	DC01, DC02, DC08, DC11
FC13	Product Value Density	Value per volume or weight of product.	DC02
FC14	Digital Maturity	Capabilities and IT infrastructure of the organisation	DC07, DC09, DC11, DC14, DC16

FC01: Organisation Size

Size of the organisation. This characteristic is relatively simple but may be defined in terms of several distinct metrics. It influences several decision situation characteristics.

- DC02 Number of Decision Variables: Larger organisations may have more decision variables, as they tend to own more resources and produce more distinct products.
- DC05 Decision Frequency: In larger organisations, which are subdivided into distinct sections, similar decisions are made more often. Larger organisations may also be more procedural and thus have more formalised decision-making.
- DC06 Decision Routine: Larger organisations tend to have more formalised processes, leading to an overall higher decision routine in the sense that decisions are standardised and prescribed.
- DC07 Development Capabilities: Larger organisations tend to have more IT employees and users, resulting in overall higher development capabilities.
- DC11 Data Acquisition Intensity: Due to their larger size and more fractured organisation, the amount of different data necessary and the effort necessary may be larger.
- DC14: Larger organisation may have more computational resources available.
- DC15: Due to the more fractured nature, larger organisations may require better explanations for decisions.

Relevant Metrics:

- Yearly Turnover: The turnover generated by the company. Can be measured over multiple years to increase stability. Can be specified to turnover associated with the production of physical products.

- Number of Employees: The number of permanent employees of the company. To account for part time employees full time equivalents can be used. Can be specified to direct employees or employees associated with value creation.
- Number of Sites: The number of distinct locations, i.e. legal addresses, the organisation owns. Can be specified to locations with physical value creation.
- Company Valuation: The financial valuation of the organisation, for example based on stock prices. Alternatively, the balance sum may be used.

FC02: Decision Centrality

The degree to which decisions similar to the examined one are made centrally or in distributed manner. The degree of centralisation is continuous. Distribution of decisions may occur across product groups, locations, markets, and organisational functions. More distributed decisions allow for the consideration of specific characteristics of local systems. This may affect several decision characteristics:

- DC01 System Linearity: In more distributed, systems, which are distinguished by their characteristics, suitable specific linearisation's may be applicable, which are not applicable for centralised decisions.
- DC02 Number of Decision Variables: Decisions made centrally can be concerned with larger overall systems and thus more decision variables.
- DC03 System Expertise: Decentralised decisions may allow for better knowledge of the DMC regarding the local system.
- DC05 Decision Frequency: In centralised decision-making, similar decision may be made more often.
- DC06 Decision Routine: Centralised decisions can be better standardised, leading to overall higher decision routine.
- DC07 Development Capabilities: The development capabilities available for centralised decisions tend to be higher.
- DC08 Perspective Diversity: In centralised decisions more different interests must be satisfied.
- DC15 Desired Explainability: In centralised decisions, the interactions within the larger systems may be more complex, the system expertise lower, and more interests involved, so the desire for explainability is higher.

Relevant Metrics:

- Roles of centralised and localised decision makers in decision processes: The degree to which central or local decision makers can influence the decision.
- Localisation of performance measures: Degree to which the outcomes of the decision are measured against local performance or global overall performance.

FC03: Market Relation

Point in the product creation process, at which the product is assigned to a customer and specified according to their interests. This is also commonly referred to as the order decoupling point. Typical instances are EtO, MtO, AtO and MtS. This changes the degree to which configuration decisions are impacted by customers directly. Also, earlier decoupling is associated with products that are individualised for the customer, which may affect configuration decisions:

- DC01 System Linearity: Earlier decoupling points and higher individualisation are associated with more diverse productions processes, which decrease the linearity of the system.
- DC04 Uncertainty: A more immediate connection of production processes to customers increases the dependency on them and thus increases market-side uncertainty.
- DC08 Perspective Diversity: Especially in very high individualisation, the development and sales are more involved in the production process increasing perspective diversity in configuration decisions.

Relevant Metrics:

- Share of individualised products: Share of products that have a degree of customer specific engineering effort invested.
- Assigned production time: Ratio of production time after decoupling point and production time before decoupling point.

FC04: Resource Share

Share of production costs caused by costs of capital spend on production resources. Higher values of this indicate very high degrees of automation and tend to align with less volume flexible production, as resources have relatively long investment circles. This may affect the dynamics of configuration problems:

- DC02 Number of Decision Variables: A resource share may require the integrated consideration of decisions with very different time scales, as volatile order

numbers must be considered in investment decisions. This can increase the number of decision variables in those problems.
- DC04 Uncertainty: The susceptibility to unforeseen changes especially in terms of market demand is increased by a higher inflexibility due to capital intensity, thus increasing overall uncertainty.
- DC12 Time Horizon: Due to the inflexibility of automated resources, the time horizons that must be considered may tend to be longer, especially for very high investment resources.

Relevant Metrics:

- Share or capital costs of production costs: Share of costs that is attributable to depreciation of production resources.

FC05: Product Heterogeneity

The degree to which products differ from each other in terms of their production requirements. These differences may affect the overall production equipment and its capabilities. It may also affect the addressable markets for various products, as well as decision objectives:

- DC02 Number of Decision Variables: More heterogeneity may lead to a higher number of decision variables, as clustering becomes more difficult and more different resources must be considered.
- DC08 Perspective Diversity: Higher heterogeneity can lead to higher perspective diversity, as the heterogeneity is reflected in the structure of the organisation.
- DC11 Data Acquisition Intensity: The amount and effort to acquire the necessary data may increase as more distinct systems and data sources are relevant.

Relevant Metrics:

- Average Number of shared components: The number of components shared between products can indicate their commonality.
- Average Number of Shared Production Resources: The number of production resources which can be shared between products may indicate their commonality.
- Price Variation: A higher variation in prices may indicate higher heterogeneity of products.

- Primary Performance Variation: For products with similar functions, the variation in their primary performance measures may serve as a measure of variation.

FC06: Production Lead Time

The time from start of production of a product to its finalisation. Due to complex supply chains, this can be difficult to assess, but a rough estimate is sufficient, as it expresses the susceptibility to demand or supply shocks:

- DC04 Uncertainty: Longer lead times make reactions to changes in demand or supply more cumbersome thus increasing the importance of uncertainty in configuration decisions.
- DC12 Time Horizon: Longer lead times require planning horizons scaled appropriately.

Relevant Metrics:

- Global Lead Time: Lead time considering the entire supply chain. Can be difficult to measure due to limited transparency and complexity.
- Internal Lead Time: Duration of the internal production process. Is affected by the degree of vertical integration.

FC07: Product Stability

The average time unchanged products are sold in a market without being replaced by newer or superior products or being pushed to lower price markets. More stable products can decrease the risk of investments and allow for a less dynamic configuration decision:

- DC04 Uncertainty: Higher stability decreases the uncertainty associated with configuration decisions.
- DC05 Decision Frequency: If market conditions are also relatively stable, the necessary planning frequency can be reduced significantly.
- DC12 Time Horizon: The time horizon for stable products may be longer.

Relevant Metrics:

- Average Production Run: Average time comparable products were produced in the past years. May not capture future developments.
- Share of Development Spending: Lower development spending in the market may indicate higher stability.

- Resale Value of Like New Products: When the product is stable over time resale values remain comparable to new products. May be affected by speculation.

FC08: Vertical Integration

Share of value creation activities of a final product performed by the company. Higher integration may lead to more diverse processes, but also better control over supply:

- DC01 System Linearity: The more diverse processes and relationships associated with high vertical integration may lead to reduced linearity of the considered systems.
- DC03 System Expertise: Higher vertical integration is often associated with increased knowledge regarding dependencies between different processes.
- DC04 Uncertainty: In vertically integrated organisations, the uncertainty due to supply is somewhat reduced.
- DC08 Perspective Diversity: Higher vertical integration may lead to more diverse stakeholders in configuration decisions, especially if plants deliver to other plants.
- DC11 Data Acquisition Intensity: In highly integrated production the number of distinct systems inside the organisation may be higher, but data may be more available in terms of the overall supply chain.

Relevant Metrics:

- Material Cost Share: Share of production costs caused by material, may be used as an inverse of vertical integration.
- Share of Internal Production Lead Time: Share of the lead time of a product that occurs inside the focal company.

FC09: Production Volume

Number of products produced. Higher volumes are associated with increased standardisation and more available information:

- DC01 System Linearity: Higher volumes are associated with dedicated production equipment with stable production times, more suitably described by linear equations.
- DC02 Number of Decision Variables: Higher volumes may require more resources and overall, more decision variables.
- DC11: In more standardised production associated with higher volumes, the availability of data may be higher.

Relevant Metrics:

- Average Production Rate: The number of products produced per time. May be specified to a plant or line.

FC10: Production Technology Stability

Degree to which the production technologies employed remains stable across multiple product generations. In case of high stability, the same equipment may be used, whereas instable technology changes, even within a product generation

- DC01 System Linearity: Stable technology may lead to more linear overall system behaviour, as dynamic trade-offs do not have to be considered to the same extent.
- DC02 Number of Decision Variables: In more stable technology environments fewer different equipment and options need to be considered jointly.
- DC03 System Expertise: In more stable technological environment, a higher knowledge of the system behaviour may be acquired over time.
- DC04 Uncertainty: If the technology and equipment is well known, internal uncertainties may be curbed.
- DC05 Decision Frequency: More stable production technology may require fewer configuration decisions, as fewer changes in the equipment are necessary.
- DC08 Perspective Diversity: Technological stability may allow for a clearer separation of decisions between functions and thus lower perspective diversity.
- DC11 Data Acquisition Intensity: Higher stability may lead to lower data demands and fewer distinct sources from which to acquire data.

Relevant Metrics:

- Average Equipment Share between Generations: The degree to which the same equipment is used between product generations.
- Average Costs to Transform Equipment to new Generation: The costs necessary if equipment is changed or made compatible with newer products.

FC11: Commoditisation

Degree to which the product is primarily differentiated on the market by its price. In commodity products the decisions are primarily aimed at increasing production efficiency, lowering costs:

- DC01 System Linearity: The production costs are largely well described by linear equations, so a focus on this objective may lead to higher linearity in configuration decisions.
- DC08 Data Acquisition Intensity: The necessary data requirements for decisions may be reduced if the problem is primarily focused on costs.

Relevant Metrics:

- Sales Margin: Commodity products usually have very low margins, so the margin may serve as a good indicator, especially when margins across the industry are considered.
- Customer Sentiment: The sentiment customers have towards the product and specifically the trade-offs between products may be considered.

FC12: Production Splits

Production that is split across multiple sites. Such splits increase the coordination effort between sites but can also increase flexibility. In case of volume splits, similar equipment is used at multiple sites, so coordination in terms of standardisation and capacity planning is necessary. In case of process splits, the sites depend upon each other, so coordination regarding order management and quality is necessary. By contrast, type splits produce sites that are less dependent on each other. In the following, the precise nature of splits is addressed in the mechanisms.

- DC01 System Linearity: Especially in process split situations, the dependencies between sites are manifested in terms of product quality and delivery reliability, which are only partially captured in linear expressions.
- DC02 Number of Decision Variables: Process and volume splits lead to large interconnected systems of sites that must be considered in conjunction, increasing the number of decision variables in configuration decisions.
- DC08 Perspective Diversity: Process and volume splits lead to more diverse perspectives in configuration decisions, either through competition between sites for volumes or coordination between internal component supplier and buyers.
- DC11 Data Acquisition Intensity: Process and volume splits may require a joint consideration in configuration decisions, while requiring a larger set of data sources that need to be considered.

Relevant Metrics:

- Sites per Type Rate: Average ratio of number of final production sites per product type out of available sites. Measures volume split.
- Sites per Product Rate: Average ratio of number of production sites involved in product instances out of available sites. Measures process split.
- Types per Site Rate: Average ratio of number of final product types per productions site out of all product types. Measures type split.

FC13: Product Value Density

Weight of a product or component per transportation unit. Usually measured in terms of volume for land and sea freight and weight for air freight. Higher value density lowers the relative importance of transportation costs. For very low value density, which leads to highly localised production, whereas very high value density increases the importance of local production factors. This mainly affects the size of considered systems and perspective diversity:

- DC02 Number of Decision Variables: Low value density may lead to very independent localised production, thus decreasing the number of decision variables in configuration decisions.
- DC08 Perspective Diversity: Low value density may lead to smaller independent networks and a dominance of logistic considerations. Very high value density may lead to globally interconnected networks where logistic considerations play a subordinate role in terms of costs. Thus, the perspective diversity may be the highest for medium value density products.

Relevant Metrics:

- Volumetric value density: Product price or costs per volume. Most relevant for land and sea freight.
- Specific value density: Product price or costs per weight. Most relevant for air freight.

FC14: Digital Maturity

The degree to which the company has advanced digital capabilities utilised in business and manufacturing processes. This includes the availability of data, the use of digital tools and the capabilities of both IT specialists and other members of the organisation. This may significantly alter the decision situation in terms of using DSS:

- DC07 Development Capabilities: Higher digital maturity may be associated with more capable and experienced developers and thus increased capability to develop new digital tools.
- DC09 Achievable Accuracy: Higher digital maturity may lead to better quality of available data on several aspects in turn increasing the achievable accuracy of decision making.
- DC11 Data Acquisition Intensity: Higher digital maturity may reduce the effort necessary to acquire data needed for decision making.
- DC14 Computing Capabilities: Higher digital maturity may be associated with more available computing capabilities both in terms of on premise and cloud computing, as these capabilities are also necessary for other digital solutions.
- DC16 Model Expertise: Higher maturity may be associated with higher model expertise, as users are more acquainted with digital planning tools.

Relevant Metrics:

- Share of Digital Business Processes: Share of business processes that are fully or partially digitalised. May be a good indicator of digital maturity. This is potentially biased towards larger companies, with more standardised processes.
- Production Data Captured: The amount of data captured per production step. May be inflated through high frequency or high data volume measurements.
- IT Cost Share: Share of IT costs in overall business overhead. May depend on association of costs. May be inflated by expensive but inefficient digitalisation.

A2.3 Objective Structure

In the following, a reference structure for PNC tasks is discussed. This structure is organised based on the overall objectives introduced in 2.1.4.1. Each of the five main categories contains a number of objective types, which in turn may have subvariants. In the following, each objective type, its noteworthy variants, the effects on the decision situation and noteworthy applications in existing approaches is discussed. An overview of these objectives in provided in Table A 4, as well as an estimation of effects on DCs[86].

[86] It should be noted that the effects on DCs cannot be considered purely additive. For example, delivery objectives may require similar data to flexibility objectives, so the overall effect on data acquisition intensity of using both is lower, than the table suggests. Furthermore, the assessment starts from the perspective of a typical, relatively simple PNC decision.

Table A 4: Reference Objective Structure in Production Network Configuration

Objective Category	Objective Type	Exemplary Measures	Implications on DC01: System Linearity	DC02: Number of Decision Variables	DC04: Uncertainty	DC08: Perspective Diversity	DC09: Achievable Accuracy	DC10: Objective Quantifiability	DC11: Data Acquisition Intensity
Company Success	Profit	Net Present Value, Profitability, Profit Margin		+	+	+		+	+
	Viability	Likelihood of Survival, Diversity of Dependencies, Static Monetary Viability	--	++	++	++	--	-	++
	Competitive Position	Market Share, Price Position, Competitive Strength, Game-Theoretical Value	--	+	++	++	-	-	++
	Company Value	Discounted Cash Flow, Economic Value Added, Tobin's Q, Real Options Valuation	--	+	++	++	-	-	+
Operational Objectives	Costs	Static Total Costs, Net Present Costs, Equivalent Annual Costs, Unit Production Costs, Activity-Based Costing Evaluation, Risk-Adjusted Expected Costs, Emission Costs, Penalty Costs			-	-		++	
	Utilisation	Capacity Utilisation Rate, Overall Equipment Efficiency		-	--	--	++	++	-
	Throughput	Throughput Rate, Order-to-Delivery Time, Inventory Turnover	-	+	+	+	-	++	+
Customer-related Objectives	Quality	Defect Rate, First Pass Yield		+		+	+	+	+
	Delivery	Average Delivery Time, Delivery Reliability, Delivery Lead Time Variability, Expedite Frequency	--	+	+	+	+	+	+
	Flexibility	Volume Flexibility, Sourcing Flexibility, Variant Flexibility, Delivery Flexibility	-	+	+		-	-	+
	Innovation	Time-to-Market, Product Introduction Rate	-	+	+	+	-	-	+
	Service	Service Proximity, Mean Time to Repair/Replace	-	+	-		+	-	+
Dynamic & Structural Objectives	Dynamic Capabilities	Adaptability, Internal Flexibility, Value at Risk, Robustness, Recovery Time, Resilience Loss	--	+	++		-		++
	Complexity	Network Entropy, Coordination Costs	-	+	+	+	--	-	+
	Knowledge Protection	Intellectual Property Risk, Supplier Intellectual Property Exposure, Sensitive Process Protection	+		+	+	-	-	+
ESG Objectives	Environmental Stewardship	Global Warming Potential, Water Consumption, Ecological Hazard, Biodiversity Effect, Captured Land		+	+	+	-	-	++
	Societal Responsibility	Worker Safety, Job Security, Living-Wage Coverage, Community Impact		+		+	-	-	++
	Corporate Governance	Corruption Exposure, Supplier Compliance, Regulatory Complexity		+	+	+	-	--	++

Company Success

In the following the company success objectives are detailed. They consider the entire organisation and its successfulness. Profit is a monetary way to measure the success of a configuration decision, which considers both costs and turnover generated.

Competitiveness contextualises the decision with regard to the competition in a specific market. Viability considers the likelihood of long-term survivability of the organisation. Company value, or more specifically change of company value, measures how a decision changes the monetary value of the organisation. These objectives all require a very comprehensive consideration of the organisation and thus increase the overall complexity of decision-making processes.

Profit

Profit objectives measure the monetary value a decision provides in terms of both costs and revenues. That implies a consideration of both the operational objectives and sales performance achieved through improving customer related objectives. The resulting complexity and uncertainty of results depend heavily on the considered mechanisms by which changes in sales are achieved. In some cases, sales performance may be describable as a univariate function of customer related objectives or a superposition of them. In many cases though, sales may be the result of a nonlinear combination of several factors and even be influenced by the behaviour of the competition. Profit also does not consider the long-term effects of a decisions in terms of the overall competition system. Of the company success objectives, it is however the most suitable for quantification.

Variants of Profit objectives:

- Static Profit Calculation: Considers the average revenues, operative costs, and depreciation costs in a hypothetical stable situation. Requires the least computation and data.
- Net Present Value (NPV): Quantifies the dynamic value $V^{(NPV)}$ of a decision by discounting future cash flows R_t depending on the discount rate i and the investment horizon N. i ad N can be adjusted to reflect different opportunity regimes.

$$V^{(NPV)}(i,N) = \sum_{t=0}^{N} \frac{R_t}{(1+i)^t} \qquad \textit{Equation A 44}$$

- Equivalent Annual Costs (EAC): Lifetime adjusted yearly costs $v^{(EAC)}$ associated with an investment. This evaluation is particularly useful when comparing investments with different expected lifetimes used to determine N. As many PNC decisions consider a fixed time horizon, the use is limited.

$$v^{(EAC)}(i,N) = -\frac{i(1+i)^N}{(1+i)^N - 1}\sum_{t=0}^{N}\frac{R_t}{(1+i)^t} \qquad \textit{Equation A 45}$$

- Real Options: Extension of NPV that considers uncertainty in the decision process and assumes the organisations reacts to the realisation of uncertain developments. Only possible in conjunction with some form of stochastic modelling.
- Product Contribution Margin: When most fixed costs of the organisation are not considered the contribution margin of a product may be considered as an objective. It is particularly applicable, if a product type is dominant or its success is a central concern of the decision.

Implications for decision characteristics:

- DC01 System Linearity: As profits only consider monetary aspects, the linearity is not drastically affected. However, depending on the considered mechanisms in terms of sales performance linearity may not be given.
- DC02 Number of Decision Variables: Profit consideration requires a broad consideration of the organisation as a whole, so the number of decision variables tends to increase.
- DC04 Uncertainty: Profit considerations heavily depend on market developments, so the importance of uncertainty is increased when considering profit.
- DC08 Perspective Diversity: Profit considerations require at least an inclusion of the value creating function increasing the perspective diversity.
- DC09 Achievable Accuracy: The data quality on monetary aspects is typically comparatively high, so that the achievable accuracy for profit considerations is not negatively affected.
- DC10 Objective Quantifiability: The quantifiability is high as the objective is monetary.
- DC11 Data Acquisition Intensity: The inclusion of several distinct functions and the consideration of markets leads to high data acquisition intensity.

Viability

Viability describes the long-term successfulness of the organisation following an infinite game conceptualisation. Thus, it focuses primarily on how decisions alter the likelihood of continued successful existence of the organisation. Such considerations are very threat-driven, thus ensuring the continuation of markets, suppliers, resources, and relationships the organisation depends upon. Due to its stochastic nature and very comprehensive and complex view, such an objective is difficult to operationalise, but may in certain cases be used, especially when a limited type of threads and strategies to address them are available. For example, a dominant purchasing organisation may purposefully ensure multiple suppliers per good survive by giving each a share of orders. While the immediate costs may be higher than awarding all order to the cheapest supplier, this strategy ensures the future competitiveness of the markets. Another example is high investment, high volume production resources, which may not have a positive present value, but are necessary to remain competitive at all in a certain region. In effect, viability objectives are very similar to some structural & dynamic objectives like robustness and resilience but focusses more on the outcome than the capabilities. Overall, the viability of a whole organisation is difficult to assess and may not align well with more conventional strategic objectives.

Variants of viability objectives:

- Likelihood of survival: Determines the likelihood that the organisation is capable to exist in a given timeframe. Requires a comprehensive consideration and assessment of potential paths for the organisation to relinquish.
- Diversity of Dependencies: Measures the extent to which the organisation's critical inputs, markets, or partners are spread across multiple, uncorrelated sources of risk (e.g., different currencies, regions, or political regimes). A higher diversity score implies fewer single-point failures.
- Static Monetary Viability: Assesses survivability using a single-period financial snapshot. Typically involves key liquidity and solvency ratios (e.g., current ratio, debt-to-equity, free cash-flow margin) under a "no-growth" baseline. Requires only balance-sheet and cash-flow data but omits dynamic scenario shifts and structural interdependencies.

Implications for decision characteristics:

- DC01 System Linearity: Viability requires the consideration of very complex relationships and effects on likelihood. Thus, using it as an objective decreases linearity significantly.
- DC02 Number of Decision Variables: Due to the size of the system to be considered, and the complication of uncertainties viability significantly increases the number of decision variables to be considered.

- DC04 Uncertainty: Viability focuses heavily on the result of uncertain developments, thus significantly increasing its importance.
- DC08 Perspective Diversity: Viability considerations often require the consideration of several to all internal functions and external factors that act on the organisation, thus significantly increasing perspective diversity.
- DC09 Achievable Accuracy: By its nature viability seeks to assess future developments that may be drastically altered by minor changes. Therefore, the achievable accuracy is significantly diminished.
- DC10 Objective Quantifiability: The change of viability due to configuration decisions is challenging to quantify.
- DC11 Data Acquisition Intensity: Due to the number of factors to be considered, the data acquisition intensity is significantly increased when viability is an objective.

Competitive Position

Competitive Position objectives measure an organisation's relative standing in its markets by benchmarking both internal performance (e.g., volume, cost, brand strength) and competitors' actions. Unlike purely internal metrics, they treat the market as an interactive arena where rivals react strategically. Incorporating competitive-position objectives thus demands market and competitor data-. For strategic-interaction variants, explicit modelling of payoff functions and best-response behaviours is necessary. This broadened scope tends to introduce nonlinearity, additional decision variables, and higher data requirements, but it yields insights into how configuration choices influence, and are influenced by, the strategic moves of others.

Variants of competitive position objectives:

- Market Share: Proportion of the market captured by the organisation. Can also be used as growth rate or relative to a market leader.
- Price Position: Average selling price in comparison to key competitors. Alternatively relative cost position can be used.
- Competitive Strength: Weighed sum of factor ratings in customer-related objectives vis-à-vis the competition.
- Game-Theoretical Value: Captures position in competitive game, for example as Nash equilibrium payoff or deterrence value.

Implications for decision characteristics:

- DC01 System Linearity: Strategic-interaction functions and feedback loops create pronounced nonlinearity; even static ratios can embed thresholds.
- DC02 Number of Decision Variables: Requires modelling both own and competitors' parameters significantly increases variables.
- DC04 Uncertainty: External market data and competitor reactions introduce high uncertainty.
- DC08 Perspective Diversity: Necessitates integrating market, competitor, sales, and marketing perspectives, substantially increases diversity.
- DC09 Achievable Accuracy: Competitor data are often estimated or lagged, reducing achievable accuracy.
- DC10 Objective Quantifiability: While metrics like market share and price ratios are quantifiable, several relevant indicators depend on subjective scoring.
- DC11 Data Acquisition Intensity: High effort to gather and validate market-level and competitor information.

Company Value

Company Value objectives assess how configuration decisions alter the total monetary valuation of the organisation as perceived by investors or acquirers. Unlike profit, which measures periodic earnings, and viability, which gauges long-term survival probability, company value combines projected cash flows, cost of capital, and market expectations. Incorporating company-value metrics requires explicit valuation models, forecasts of financial performance, and assumptions about investor risk preferences. These elements increase modelling complexity, introduce long-time uncertainties, and demand both internal financial data and external market comparisons.

Variants of company value objectives:

- Discounted Cash Flow (DCF): Sum of forecasted discounted cash flows R_t plus a terminal value based on perpetual growth rate g

$$V^{(DCF)}(i,N) = \sum_{t=0}^{N} \left(\frac{R_t}{(1+i)^t}\right) + \frac{R_{N+1}}{(i-g)(1+i)^N} \qquad \text{Equation A 46}$$

- Economic Value Added: Value added beyond the organisations cost of capital.
- Tobin's Q: Ratio of the organisation's market value of assets to their replacement cost.

- Real Options Valuation: Extends DCF by valuing managerial flexibilities (e.g., capacity expansion, abandonment) as financial options. Requires stochastic process assumptions for underlying uncertainties and option-pricing techniques.

Implications for decision characteristics:

- DC01 System Linearity: Most variations are largely linear, but option valuation introduces nonlinearity.
- DC02 Number of Decision Variables: Moderately increased due to financial forecasting variables.
- DC04 Uncertainty: Long-term cash-flow projections, discount-rate selection, and market multiple volatility significantly heighten uncertainty.
- DC08 Perspective Diversity: Requires integration of operational forecasts, capital-structure considerations, and investor-market viewpoints, broadening the set of perspectives.
- DC09 Achievable Accuracy: Moderately lowered due to dependence on forecast quality and market volatility.
- DC10 Objective Quantifiability: Relatively high, objectives are quantifiable but may carry biases.
- DC11 Data Acquisition Intensity: Moderately increased effort to gather forecasts for internal and external developments.

Operational Objectives

In the following operational objectives are discussed. These objectives are primarily concerned with the efficiency of value creation in terms of using monetary resources or available capacity. These objectives are directly influenceable by the production domain. Using the objectives assumes that the production demand is predetermined and only the manner of its fulfilment may be shaped by a decision.

Costs

Cost describes the monetary efforts necessary to achieve a predetermined production demand. Several cost types need to be considered, such as material, energy, infrastructure, personnel, equipment, logistic and capital costs. In production systems these costs behave largely linearly. Costs are the most used objective in PNC tasks. Different cost measures differ in comprehensiveness, consideration of dynamics, life cycle costs, and reference unit.

Variants of cost objectives:

- Static Total Costs: Sum of all relevant costs in a stable stead state without any time discontinuing.
- Net Present Costs (NPC): Discounted sum of cost streams C_t based on the period t they occur in and the discounting rate i:

$$C^{(NPC)}(i,N) = \sum_{t=0}^{N} \frac{C_t}{(1+i)^t} \qquad \textit{Equation A 47}$$

- Equivalent Annual Costs: Converts NPC into a uniform annual value. This reflects differing asset lifetimes and makes them comparable.

$$c^{(EAC)}(i,N) = \frac{i(1+i)^N}{(1+i)^N - 1} \sum_{t=0}^{N} \frac{C_t}{(1+i)^t} \qquad \textit{Equation A 48}$$

- Unit Production Costs: Determines average costs per unit produced.
- Activity-Based Costing Evaluation: Allocates overheads and indirect costs to products based on their share of predetermined cost drivers like number of orders, production times, number of consumed materials, etc.
- Risk-Adjusted Expected Costs: Probability $\mathbb{P}(\omega)$ weighted scenario costs C_ω with risk premium for variance λ

$$C^{(RAEC)}(i,N) = \sum_{\omega\in\Omega} \left(\mathbb{P}(\omega)C_\omega + \frac{\lambda}{N_\Omega} C_\omega^2\right) - \frac{\lambda}{N_\Omega^2} \left(\sum_{\omega\in\Omega} (C_\omega)\right) \qquad \textit{Equation A 49}$$

- Emission Costs: Monetises greenhouse gas emissions and equivalents using a carbon emission price.
- Penalty Costs: Captures contractual fines incurred based on stockouts, late deliveries or quality failures.

Implications for decision characteristics:

- DC01 System Linearity: Most cost objectives are additive and therefore linear. However, considering economies of scale or nonlinear factors can introduce nonlinearities.
- DC02 Number of Decision Variables: Costs do typically have no specific impact on decision variables.
- DC04 Uncertainty: Depending on the type of cost measures considered.
- DC08 Perspective Diversity: A purely cost driven focus tends to demote perspective diversity, as it focuses entirely on quantifiable aspects.

- DC09 Achievable Accuracy: Accuracy of costs is mixed. Some aspects can be estimated with high accuracy while uncertainty and unplanned aspects of investments can introduce inaccuracies.
- DC10 Objective Quantifiability: Costs are highly quantifiable.
- DC11 Data Acquisition Intensity: Cost objectives typically result in moderate data acquisition intensity as they require high granularity, but much of the data is readily available.

Utilisation

Utilisation measures the degree to which capacity, usually of capital-intensive assets is used in production. High utilisation of those assets typically results in lower unit costs. Thus, they are used commonly in more short-term decisions where the utilised assets cannot be changed. However, utilisation can conflict with other objectives such as short lead times and responsiveness.

Variants of utilisation objectives:

- Capacity Utilisation Rate: Rate of actual output to designed rated capacity.
- Overall Equipment Effectiveness (OEE): Product of asset availability, performance, and quality rates.

Implications for decision characteristics:

- DC01 System Linearity: Utilisation objectives are typically linear or linearizable, though especially OEE can introduce nonlinearity.
- DC02 Number of Decision Variables: By limiting the consideration to utilisation, the number of decision variables can be reduced as less configurative objects are considered. However, the use of utilisation may still coincide with higher numbers of decision variables, as short-term decisions often do integrate many decision variables due to the high granularity.
- DC04 Uncertainty: Uncertainty is usually relatively low when considering short-term utilisation.
- DC08 Perspective Diversity: A pure focus on utilisation is even more reductive than costs, so perspective diversity is strongly reduced.
- DC09 Achievable Accuracy: The achievable accuracy for utilisation is high, as it is well measurable provided master data is correct and up to date.
- DC10 Objective Quantifiability: Utilisation is highly quantifiable.

- DC11 Data Acquisition Intensity: Utilisation measures focus the data acquisition into the operative domain, thereby reducing the intensity.

Throughput
Throughput measures focus on the quantity of products the GPN can provide in a given time. In specific market conditions, profits may be primarily limited by the number of sold products so that lower margins as a trade-off to higher volumes are desirable. Thereby throughput is typically considered as an objective for transformative situations where organisations try to capture as much of the market as fast as possible. Examples can be introduction of new products, not anticipated surges in demand, or conquering new markets. Its analysis typically requires high temporal granularity to accurately represent the flows in GPNs.

Variants of utilisation objectives:

- Throughput Rate: Rate of products produced per unit of time.
- Weighed Throughput: Throughput weighted by contribution margin, prioritising more profitable products.

Implications for decision characteristics:

- DC01 System Linearity: Granular consideration of throughputs requires usually nonlinear models, which may be captured by DES for example, so linearity is reduced.
- DC02 Number of Decision Variables: Additional decision variables may be introduced to account for the granularity of temporal considerations.
- DC04 Uncertainty: Uncertainty is moderately increased as the throughput is sensitive to a range of disruptions.
- DC08 Perspective Diversity: Throughput ties together several domains such production, logistics, site management, etc. Thus, perspective diversity tends to be increased.
- DC09 Achievable Accuracy: The achievable accuracy is limited by the sensitivity and non-predictability of disruptions.
- DC10 Objective Quantifiability: Throughput is highly quantifiable.
- DC11 Data Acquisition Intensity: Throughput requires extensive data on change timeliness as well as availabilities and stocks. Thus, acquisition efforts are moderately raised.

Customer-related Objectives

In the following customer-related objectives are discussed. These are objectives which can be directly influenced by production and GPN and that indirectly affect sales numbers and thereby profitability and success of the organisation. The often conflict with the previously discussed operational objectives.

Quality

Quality measures capture the fulfilment of desired product functionality. In PNC, quality rates can differ by suppliers, technologies, and sites. Quality is usually used as a complementary objective. Especially when dynamic developments are considered, like supplier development for example, quality objectives can introduce added complexity.

Variants of quality objectives:

- Defect Rate: Rate of products failing to meet specifications.
- First Pass Yield: Proportion of products passing all processes without requiring rework or scraping.

Implications for decision characteristics:

- DC01 System Linearity: Quality rates are typically linear but the inclusion of stochasticity and development paths for suppliers can introduce nonlinearity.
- DC02 Number of Decision Variables: Additional decision variables may need to be considered to address quality issues, like effort for quality control and supplier development.
- DC04 Uncertainty: The uncertainty related to quality rates is moderate.
- DC08 Perspective Diversity: Quality objectives concentrate on production and procurement, so perspective diversity is moderately increased.
- DC09 Achievable Accuracy: The achievable accuracy for failure rates is moderately high.
- DC10 Objective Quantifiability: Quality rates can be quantified relatively well but customer perception may evade quantification.
- DC11 Data Acquisition Intensity: Data acquisition intensity is moderately increased as additional data from CAQ systems and supplier databases have to be used.

Delivery

Delivery objectives quantify the speed and reliability with which customers are served by the GPN. They require extensive consideration of temporal dependencies through procurement, production, and logistics. These objectives are pursued if delivery times are critical for example in make-to-order (MtO) or assemble-to-order (AtO) environments. The variants of these objectives differ significantly in their effect on the DCs. These measures require the consideration of stochasticity and interact with buffer capacities.

Variants of delivery objectives:

- Average Delivery Lead Time: Mean time elapsed from order placement to fulfilment. Typically depends on the order penetration point, availability of materials and logistic processes.
- Delivery Reliability: Proportion of orders delivered on or before the confirmed due date.
- Delivery Lead Time Variability: Variability of lead times.
- Expedite Frequency: Ration of orders that require overtime or premium transport to meet due date. Allows capturing real efforts and connected costs that may be hidden when just considering delivery reliability.

Implications for decision characteristics:

- DC01 System Linearity: Outside of very basic mean time considerations, accurate modelling of delivery requires non-linear system representations.
- DC02 Number of Decision Variables: Considering delivery may require additional decision variables for example stock sizes, overtimes, and route alternatives.
- DC04 Uncertainty: The uncertainty related to lead times is increased though the law of large numbers usually aids in limiting the uncertainty.
- DC08 Perspective Diversity: Lead times require consideration of multiple different domains, at least production and logistics, but possible other aspects of the order processing organisation.
- DC09 Achievable Accuracy: The achievable accuracy is moderately high as the fluctuations are typically well documented.
- DC10 Objective Quantifiability: The delivery objectives are well to very well quantifiable.
- DC11 Data Acquisition Intensity: Data acquisition intensity is increased as granular data of order flows and storage capacities is necessary.

Flexibility
Flexibility measures how well the organisation can accommodate changes in requested volume, product configurations, and delivery timing. In many cases, these objectives require detailed modelling of temporal considerations or product market fit. These objectives are typically used as secondary objectives or constraints.

Variants of flexibility objectives:

- Volume Flexibility: Relative output volume range that can be realised for a given planning horizon.
- Sourcing Flexibility: Share of products that can be provided from more than one location.
- Variant Flexibility: Extent to which products can be adapted to customer desires either within the predetermined product portfolio or product adaptions.
- Delivery Flexibility: Acceptable due date shifts.

Implications for decision characteristics:

- DC01 System Linearity: Depending on the specific type of flexibility required the system can either be relatively linear, for example for some types of volume or sourcing flexibility but require extensive non-linear aspects for others.
- DC02 Number of Decision Variables: Considering flexibility can moderately increase the number of decision variables.
- DC04 Uncertainty: Some flexibility measures can be very sensitive to available free capacity increasing the effects of uncertainty, whereas others are relatively certain.
- DC08 Perspective Diversity: Flexibility can increase the perspective diversity but is mostly encapsulated in production.
- DC09 Achievable Accuracy: The achievable accuracy is limited due to the sensitivity to system states.
- DC10 Objective Quantifiability: The overall flexibility is somewhat difficult to quantify precisely in a meaningful way.
- DC11 Data Acquisition Intensity: Flexibility objectives may require consideration of additional data sources, thus moderately increasing data acquisition intensity.

Innovation
Innovation evaluates how PNC can affect the organisation’s ability to deliver new or significantly improved products to customers. This can be impacted by decisions on

plant locations near innovation hubs and markets and the speed with which new products can move from development to production.

Variants of innovation objectives:

- Time to Market: Time between product concept freeze to first shipment.
- Product Introduction Rate: Number of products that complete industrialisation per year.

Implications for decision characteristics:

- DC01 System Linearity: Determining the time to market or rates of product introduction can require representing several non-linear aspects, especially in terms of temporal sequence.
- DC02 Number of Decision Variables: Can moderately increase the number of decision variables as additional factors outside of regular production operations have to be considered.
- DC04 Uncertainty: Introduces moderate uncertainty caused by possible disruptions or hard to predict effects of knowledge availability on innovativeness.
- DC08 Perspective Diversity: Requires consideration of several perspectives, such as development, site management, and personnel management.
- DC09 Achievable Accuracy: The achievable accuracy is limited due the limited predictability of ramp-up and development processes.
- DC10 Objective Quantifiability: The degree of innovativeness overall is difficult to capture fully in quantitative form.
- DC11 Data Acquisition Intensity: Requires additional data acquisition around knowledge and transformation times.

Service
Describes the ability of the GPN to support post-sales value creation. This can be aided by having secondary facilities or production plants in the proximity of customers. One of the most important services are repair or replacement, where the average time is often critical. Depending on the chosen metrics, the effects on modelling can differ significantly.

Variants of service objectives:

- Service Proximity: Average distance between service centres or production sites to customers.

- Mean Time to Repair/Replace: Average time required to restore or replace a product once a defect has occurred.

Implications for decision characteristics:

- DC01 System Linearity: Whereas proximity measures can be handled parametrically for a limited number of decision variables, otherwise they are quadratic. Mean repair/replace times require non-linear temporal assessments.
- DC02 Number of Decision Variables: Decision variables are increased as additional site types, and their operation are considered.
- DC04 Uncertainty: Uncertainty is limited as the proximity and mean time to repair have limited stochastic effects.
- DC08 Perspective Diversity: Perspective diversity is not affected much.
- DC09 Achievable Accuracy: The achievable accuracy is relatively high.
- DC10 Objective Quantifiability: The actual service level experienced by customers is difficult to fully quantify, though some aspects can be captured well.
- DC11 Data Acquisition Intensity: Requires additional detailed data on customers and warranty rates so data acquisition intensity is moderately increased.

Dynamic & Structural Objectives

In the following dynamic and structural objectives are considered. Whereas the previous objectives are mostly focused on outputs or the system performance, these objectives focus on the system state in regard to one specific aspect. In general, dynamic, and structural objectives are more difficult to model accurately.

Dynamic Capabilities

Describe the ability of the GPN to anticipate, absorb, and recover from disturbances while maintaining or regaining a desired performance level. They can be either considered from a capability-oriented view, where the flexibility and adaptability of the system are considered, in terms of a risk exposure metric, or in terms of performance given a level of disturbances as robustness or resilience. They are primarily concerned with assessing uncertainty and thus add complexity to the modelling task.

Variants of dynamic capability objectives:

- Adaptability: Index of resources that can be changed within a predetermined time horizon with limited costs. Must be adapted to the types of considered adaptions.

- Internal Flexibility: Flexibility in terms of product or process allocations that can be used to react to changes in the environment.
- Value at Risk: Measures the probability that a value threshold, for example for costs, is exceeded.
- Robustness: Measures the rate between reasonable worst-case scenarios and the expected performance.
- Recovery Time: Time after disruption until at least a given percentage of the nominal performance level is restored.
- Resilience Loss: Integral of performance V shortfall L compared to nominal performance $V^{(NOM)}$ over a disruption recovery period (t_0, t_1):

$$L = \int_{t_0}^{t_1} \left(V^{(NOM)}(t) - V(t)\right) dt$$ *Equation A 50*

Implications for decision characteristics:

- DC01 System Linearity: Depending on the specific dynamic capability of interest the system linearity can be considerably to strongly reduced as non-linear temporal aspects need to be considered.
- DC02 Number of Decision Variables: Decision variables are increased as multiple distinct scenarios need to be considered.
- DC04 Uncertainty: Uncertainty is the focus of these objectives and thus increased drastically in the models.
- DC08 Perspective Diversity: Perspective diversity is not affected much.
- DC09 Achievable Accuracy: The achievable accuracy is moderately limited due to the high uncertainty.
- DC10 Objective Quantifiability: The dynamic capabilities can be quantified reasonably well though some aspects especially considering capabilities are difficult to measure.
- DC11 Data Acquisition Intensity: Data acquisition intensity is increased due to data demand for disruption estimations and recovery plans.

Complexity

Measures the structural and managerial complexity of the GPN, which may add overhead costs, make reactions more cumbersome, and finding optimal solutions and configurations more difficult. Explicitly modelling these effects can help to represent drawbacks of more intricate systems.

Variants of complexity objectives:

- Network Entropy: Shannon entropy of the production network configuration or material flows.
- Coordination Costs: Monetary estimate of overheads caused by the number of site interfaces.

Implications for decision characteristics:

- DC01 System Linearity: Negatively affected due to non-linear system complexity.
- DC02 Number of Decision Variables: Moderately increased as additional system components, such as overhead types and interfaces between sites have to be considered.
- DC04 Uncertainty: Moderately increased as the actual effects of individual configurational decisions on lived complexity are difficult to predict.
- DC08 Perspective Diversity: Perspective diversity is moderately increased as additional functions have to be considered.
- DC09 Achievable Accuracy: The achievable accuracy in predicting actual complexity is very limited.
- DC10 Objective Quantifiability: The degree to which complexity is accessible to quantification is limited.
- DC11 Data Acquisition Intensity: Increased due to additional data demand to assess managerial overheads.

Knowledge Protection

Evaluates how effectively the intellectual property (IP) of the organisation, for example, proprietary technologies, manufacturing details, and product information, is protected from involuntary disclosure. This can be affected by locating critical production processes in areas with strong IP enforcement and collaborating with trusted partners.

Variants of knowledge protection objectives:

- Intellectual Property Risk: Weighted score of country specific IP enforcement levels. Weights should reflect the corresponding exposure criticality of processes and allocated products.
- Supplier Intellectual Property Exposure: Proportion of outsourced components at suppliers with subpar IP risk ratings.

- Sensitive Process Protection: Fraction of processes classified as high knowledge value located in high IP enforcement sites.

Implications for decision characteristics:

- DC01 System Linearity: Linearity is of these objectives is largely given.
- DC02 Number of Decision Variables: Largely unaffected as primarily additional parameters are needed.
- DC04 Uncertainty: Moderately increased as the level of actual IP protection is difficult to predict in future developments.
- DC08 Perspective Diversity: Increased as additional functions have to be considered to assess IP criticality and trustworthiness of partners.
- DC09 Achievable Accuracy: Negatively affected as trustworthiness, protection, and criticality are difficult to assess accurately.
- DC10 Objective Quantifiability: Limited, as quantifying actual IP exposure is difficult.
- DC11 Data Acquisition Intensity: Increased as both criticality of processes and IP protection and trustworthiness of suppliers has to be assessed.

ESG Objectives

In the following section, environmental, social, and governance (ESG) objectives are discussed. Organisations pursue these objectives as part of their mission, to align with current legislation, and the preferences of their investors, employees, and customers. Many of the issues behind these objectives are complex and evade simple quantification. Nevertheless, organisations may carefully consider their contributions to at least some of those objectives. Particularly in recent years, legislative enforcement of such considerations has become more prominent.

Environmental Stewardship

Evaluates the effect of PNC decisions on the environmental impact of the organisation. This impact may be borne out across the entire product life cycle, so sourcing, production, transportation, use, and disposal. Several dimensions of environmental impact can be considered, ranging from global warming, pollution of nature, biodiversity loss, land degradation and erosion, water consumption, land capture, etc. Each of those has to be assessed according to the organisation's priorities and its impact. In the following only the most prominent aspects are explicitly considered. Incorporating those objectives into PNC tasks varies by the type of impact considered.

Variants of environmental stewardship objectives:

- Global Warming Potential: Total greenhouse gas emissions expressed as CO_2 equivalent (CO_2e) aggregated across scope 1, 2, and 3.
- Water Consumption: Consumed volume of water, usually distinguished by source and purpose and weighed according to water-stress factors.
- Ecological Hazard: Score of toxic releases, acidification, eutrophication, photochemical smog.
- Biodiversity Effect: Area- and time-weighted habitat impact or number of endangered species affected.
- Captured Land: Land area committed to facilities, optionally adjusted by use intensity factors.

Implications for decision characteristics:

- DC01 System Linearity: The effects can be reasonably well represented in linear fashion.
- DC02 Number of Decision Variables: Some additional decision variables may be introduced by considering mitigation strategies for environmental impacts.
- DC04 Uncertainty: Moderately increase uncertainty due to unclear effects of ecological hazards and missing knowledge on scope 3 emissions.
- DC08 Perspective Diversity: Increased as several additional stakeholders need to be introduced.
- DC09 Achievable Accuracy: The achievable accuracy is mainly limited by missing data on detailed emissions and localised effects.
- DC10 Objective Quantifiability: Though some aspects like global warming potential can be quantified reasonably well, others, like biodiversity loss are difficult to quantify.
- DC11 Data Acquisition Intensity: High, several stakeholders along the supply chain have to be considered and corresponding data has to be aggregated.

Societal Responsibility
Captures the effects of PNC decisions on people in the organisation, along the supply chain, in stakeholder groups, and society at large. They can include hard measurements like worker safety and perception-based indices. Overall, these objectives are mostly qualitative.

Variants of societal responsibility objectives:

- Worker Safety: Measured as total recordable incident rate, can be weighted by exposure or severity.
- Job Security: Ratio of permanent to temporary contracts or employment retention rate.
- Living-Wage Coverage: Share of employees and optionally suppliers' employees earning at least a living wage calculated for their region.
- Community Impact: Local investments and procurement spend.

Implications for decision characteristics:

- DC01 System Linearity: Measures are mostly linear or linearizable.
- DC02 Number of Decision Variables: Some additional decision variables may be introduced to improve societal responsibility.
- DC04 Uncertainty: Uncertainty is limited, though especially for supplier data and community perception some additional uncertainty can be expected.
- DC08 Perspective Diversity: Introduces several stakeholders both internally and externally.
- DC09 Achievable Accuracy: Limited, especially for suppliers and qualitative scores.
- DC10 Objective Quantifiability: Many of the aspects are not fully quantifiable and rely on qualitative scoring.
- DC11 Data Acquisition Intensity: High, several stakeholders along the supply chain have to be considered and corresponding data has to be aggregated.

Corporate Governance

Gauge the influence of PNC decisions on integrity, transparency, and legal compliance of the organisation. These objectives are focused on aligning managerial behaviour with stakeholder and regulatory expectations. This aspect is particularly complex for organisations spanning multiple jurisdictions and political climates. Most of the indicators used for those objectives are qualitative.

Variants of corporate governance objectives:

- Corruption Exposure: Score of activities in regions or countries with high levels of corruption, optionally weighted by value creation volume.
- Supplier Compliance: Share of procurement volume spend with suppliers that have passed anti-corruption and or compliance audits.

- Regulatory Complexity: Number of distinct major compliance regimes the organisation operates in.

Implications for decision characteristics:

- DC01 System Linearity: Measures are mostly linear or linearizable.
- DC02 Number of Decision Variables: Some additional decision variables may be introduced to improve corporate governance.
- DC04 Uncertainty: Limited increase due to unpredictability of regulatory changes.
- DC08 Perspective Diversity: Requires integration of legal and trade compliance stakeholders.
- DC09 Achievable Accuracy: Limited, especially for suppliers and qualitative scores.
- DC10 Objective Quantifiability: Low, as most objective variants rely on qualitative scoring.
- DC11 Data Acquisition Intensity: High, several stakeholders along the supply chain have to be considered and corresponding data has to be aggregated.

A2.4 Domains in PNC Tasks

In the following, the relevant domains that play a role in PNC tasks are discussed. The domains are classified into primary and support domains according to their involvement in value creation processes. Table A 5 provides a brief description of each domain and a definition of relevant major variants of the domains. Both are expanded in the following paragraphs. Furthermore, implications of including the domain in PNC task for DSS design are elaborated.

Table A 5: Overview of Relevant Domains in PNC Tasks

Domain		Description	Variants
Primary Domains	Production	Planning, control, and operation of value-adding transformation processes.	
	Procurement & Supplier Management	Identification, selection, development and coordination of suppliers and their goods and services	Commodity procurement, highly integrated suppliers,
	Logistics	Planning and coordination of logistic operations for sourced parts, inter-site transfers, and distribution.	External logistics services, just-in-time logistics, exceptional transports
	Sales	Customer acquisition and management, planning, acquiring, and managing orders.	Commodity sales, frame-contracting, market dominance, seller’s market
	Customer Service	Management and provision of service offerings to customers.	External service, service-driven business, aftermarket production
S	Product Design	Development and design of products and components.	Configured products, engineer-to-order business

Quality Management & Control	Management and assurance of produced quality.	
Site & Resource Management	Management and coordination of local infrastructure and assets.	External infrastructure management, immovable assets
Human Resource Management	Acquisition, management, and development of personnel.	Large leasing workforce, strict worker protection laws/agreements
Strategic Management	Strategic management and coordination, coordination of other domains	

These modelling characteristics are described with regard to the main domain influences on desirable analytical capability, i.e. system linearity, number of decision variables, system expertise, perspective diversity, data acquisition intensity, and time horizon. The descriptions are qualitative, as a quantitative assessment could hardly cover the nuances of the domains. Where applicable qualifications are made regarding the interaction with specific objectives or domain variants

Production

Includes all activities directly involved or contributing to value adding processes, such as the production itself, material handling, intralogistics, maintenance, and management and coordination activities directly concerned with the aforementioned.

Modelling Characteristics:

- DC01 System Linearity: Most activities in the production domain behave largely linear, with the exception of delivery reliability.
- DC02 Number of Decision Variables: Depending on the chosen granularity, the number of decision variables in production can become very high.
- DC03 System Expertise: DMC responsible for PNC tasks are typically familiar with the specificities of production. However, if the data availability is low and production environments across sites are diverse the specific behaviours of local production systems can also be unknown to a large degree.
- DC08 Perspective Diversity: The diversity of perspectives in production is largely introduced by the interests of different sites and their personnel.
- DC11 Data Acquisition Intensity: The availability of data and effort associated with it is highly dependent on the particular production environment of the organisation. It can range from very low availability to very comprehensive data. The volume of data created in production is generally high.
- DC12 Time Horizon: Most configuration decisions within production adhere to a medium time horizon of multiple years.

Variants:

- Mass-production: In mass production, resources are associated with products or product types. Multiple production steps are directly connected. In modelling, complexity induced by the use of multiple production equipment and overlapping uses of equipment can be foregone, leading to less complex models.
- Order-based production: In order-based production, products are designed specifically for each customer. For each order only estimates of process times are available and the utilisation of equipment and subsequently overall lead times are very complex and difficult to model.

Procurement & Supplier Management

Includes all activities necessary to source the materials, components, and resources necessary for production as well as the management of long-term relations and contracts with suppliers.

Modelling Characteristics:

- DC01 System Linearity: Most aspects of procurement are largely linear, though the relation between prices and order volumes is often degressive. Long term developments of suppliers may be influenced by several factors and thus behave not entirely linear from the perspective of a sourcing organisation. Delivery reliability is typically non-linear.
- DC02 Number of Decision Variables: The number of decision variables depends on the supplier network of the sourcing organisation and the number of distinct sourced articles. It can become very high.
- DC03 System Expertise: DMC responsible for PNC tasks often only have a basic understanding of their supplier network and specifically the market dynamics of those suppliers. For long term decisions the involvement of supplier management experts can be crucial.
- DC08 Perspective Diversity: The procurement organisation is often separated from production management and follows a distinct objective structure, thus introducing additional diversity into decision making processes.
- DC11 Data Acquisition Intensity: Depending on the specific PNC task the acquisition of reliable data on suppliers can be difficult. Suppliers are typically interested to limit the amount of data shared to protect their interests and intellectual property.

- DC12 Time Horizon: Decisions affecting procurement span a broad range of time horizons. Volume related decisions can be made on short notice with a time horizon of months, while strategic supplier development and relation building requires a multi-year time horizon.

Variants:

- Commodity-procurement: When sourcing commodities, the connections to suppliers are less important, instead they are bought on open markets. In this case, prices are more susceptible to market fluctuations, but volume flexibility is typically higher.
- Highly integrated suppliers: When suppliers are tied very closely integrated with the sourcing organisation, more information on the resources and capacities are available. Typically, stocks are reduced in this case, and temporal dependencies are increased.

Logistics

All activities concerned with coordinating material flow and storage into, within, and out of the organisation. This requires the selection and coordination of multiple transport modes, the operation or use of warehouses, and the management of order routings throughout the logistics network. Typically, companies rely on a mixture of owned transport vehicles and warehouses and external services.

Modelling Characteristics:

- DC01 System Linearity: When a discrete set of locations and routes are given, logistics can be described relatively well in linear terms. However, location decisions are typically quadratic. Furthermore, tariffs and duties can be nonlinear as well.
- DC02 Number of Decision Variables: The inclusion of logistics can drastically increase the number of decision variables, especially if multiple different transportation options and intermediary storage is considered.
- DC03 System Expertise: The DMC may profit from the inclusion of logistics by better understanding dependencies between product variants and logistic costs and more detailed knowledge on non-isometric transportation costs for example. However, people responsible for production typically have a reasonable base level understanding of logistics processes.
- DC08 Perspective Diversity: The perspectives of production and logistics are typically well aligned in the sense that they focus on similar objectives and operate

in tightly connected systems. However, the objectives of the logistics system can conflict directly with the production system.

- DC11 Data Acquisition Intensity: Including logistics may require the integration of external data sources especially when considering short term decisions. In general, logistic processes are relatively well documented. Thus, the inclusion can slightly increase data acquisition intensity.
- DC12 Time Horizon: Decisions on logistics tend to have a shorter time horizon than PNC decisions themselves, as even the long-term resources like warehouses or distribution centres are faster to set-up and dismantle than factories.

Variants:

- External logistic services: Typically, most companies do not own most of the logistics fleet they employ. However, some central resources and the coordination lie within the control of the organisation. However, organisations may also elect to fully rely on external services for logistics. This means, logistic costs are contractually determined.
- Just-In-Time logistics: When applying a just-in-time concept to logistics, materials are only delivered shortly before they are required. In a just-in-sequence logistics, the materials are even delivered precisely in the order they are required. These concepts result in a much higher dependence of objectives such as utilisation and costs on delivery reliability.
- Exceptional transports: For very large products, which are very difficult to transport, route planning is a very complex process, and the associated costs do not behave in a linear fashion.

Sales

Activities concerning individual potential or existing customers, from lead generation to order fulfilment. This includes the tasks of market analysis and forecasting, technical, commercial, and contractual negotiating, and the communication with customers regarding the fulfilment of orders and possible deviations. Regarding PNC tasks, sales may be important to determine both capability and capacity demands. If considered holistically, sales may be able to describe the relationship between customer related objectives and predicted sales volumes. Furthermore, sales may be integrated when short term reconfigurations and reaction to deviations are considered.

Modelling Characteristics:

- DC01 System Linearity: The relationships between customer objectives and sales volume and revenues are often nonlinear and may depend on the behaviour of other market participants. Comprehensively capturing the market requires the consideration of a range of contingencies. However, the integration of sales may reduce the uncertainty created by market development through model-based descriptions and thus simplify the modelling to an extent.
- DC02 Number of Decision Variables: The inclusion of sales may increase the number of decision variables in two ways. It may require the consideration of scenarios, multiplying the existing number of decision variables and by requiring the consideration of additional customer related objectives which introduce further decision variables. Overall, the inclusion of sales slightly increases the number of decision variables.
- DC03 System Expertise: The inclusion of sales representatives can significantly improve understanding of the dependencies between production performance and market success. It also may decrease uncertainty, as market demand is one of the most important factors of uncertainty in production.
- DC08 Perspective Diversity: Sales departments usually follow a very different objective structure than production departments. Furthermore, they are more concerned with outside developments. Thus, including them increases the perspective diversity substantially.
- DC11 Data Acquisition Intensity: Modelling market behaviour accurately, requires the inclusion of internal and external data sources which may not align with the operations semantics. The inclusion of additional customer related objectives may also noticeably increase the intensity of data acquisition.
- DC12 Time Horizon: Decision in sales span the entire range of time horizons typical for PNC decisions. Thus, the inclusion of sales has a negligible effect on the considered time horizon.

Variants:

- Commodity sales: If the sold products can be characterised as commodities, the relation between customer-related objectives and sales performance is understood better and thus more suitable for quantitative modelling. Forecasts may also be made based on statistical methods rather than human estimations.

- Frame-contracting: So-called frame contracts are typical of some industries. They usually specify a product, the sales prices, and a volume range across multiple years. In those industries, the necessity to include sales departments into PNC decisions may be reduced as the requirements towards production are more formalised.
- Market dominance: If the organisation is dominating the market either regionally or globally, the market behaviour can be easier to predict and model.
- Seller's market: Typically, a temporary phenomenon, where the overall market demand significantly exceeds the available capacity of all vendors. In this case, the sales volume is primarily determined by the production capacity available.

Customer Service

Customer service activities include all activities directly interacting with the customer from the delivery of the product to the end of its live. These activities can be organised under various service agreements. Particularly noteworthy are activities that require an inhouse repair or remanufacturing of products and repair activities, which require components. Furthermore, in engineering intensive orders, commissioning and maintenance may require personnel normally employed in production. This may even affect the selection of production locations. Customer service also affects the consolidation of production resources, as the companies typically have to provide replacement parts for a predetermined time after regular production has stopped.

Modelling Characteristics:

- DC01 System Linearity: The inclusion of customer service typically has little influence on model linearity, aside for customer service quality as an objective, which has a nonlinear relation to the proximity to the customer.
- DC02 Number of Decision Variables: Considering customer service may slightly increase the number of decision variables as additional volumes for replacement parts need to be allocated and service personnel and resource have to be considered.
- DC03 System Expertise: Including customer service may increase the knowledge regarding the effect of customer-related objectives and various special processes. Furthermore, the consideration of end of production considerations may improve.
- DC08 Perspective Diversity: Customer service objectives can deviate in terms of the focus on costs which can conflict with the serviceability of products. In

addition, customer service is typically more concerned with proximity to the customer. Overall, the increase in perspective diversity is minor.

- DC11 Data Acquisition Intensity: Integrating customer service may require the inclusion of additional data sources, primarily internal ones. These sources may not be entirely aligned semantically with production. Thus, data acquisition intensity may increase moderately.
- DC12 Time Horizon: Decision in sales span the entire range of time horizons typical for PNC decisions. Thus, the inclusion of sales has a negligible effect on the considered time horizon.

Variants:

- External service: If services are outsourced to a third party, the integration becomes more challenging and requires alignment with procurement. Usually, multiple contractors are utilised as multiple different regions are serviced. Depending on the specifics of the contracts, specifically whether the contractors also take over the obligation to provide replacement parts, an integrated consideration of customer service may be less relevant.
- Service-driven business: In business that are mainly driven by services, such as production as a service or similar, the integration of customer service is almost mandatory and may even replace interaction with sales, as the production orders are primarily determined by customer service.
- Aftermarket production: If the production is primarily concerned with providing aftermarket parts an integration with customer service is almost inevitable. Moreover, production may be set up to utilise end of life components ready for remanufacturing, so-called cores. In this case PNC tasks may differ sharply, as the supply of cores is not controllable, resources may be provided without investment, as they are taken from regular production and spatial concerns may be more important than utilisation.

Product Design

Product design comprises the corporal activities concerned with conceptualising, designing, and specifying the product portfolio. This includes product-related research, strategic portfolio design, product family architecture, and product design and specification. These activities intersect with production, as far as they define the desired outcome of the production process. The design should therefore be aligned with the available production capabilities and capacities, so that efficient production is possible.

Network configuration not only intersects with the design of individual products, but also the portfolio, as a whole and its relation to different markets. Depending on the production location with a unique set of factor costs, different production technologies may come to bear, necessitating adaptions of the product design. Integrating product design into PNC tasks, may enable more opportunities for efficiency and reduce uncertainty regarding future developments. However, it may also introduce a large degree of complexity into PNC.

Modelling Characteristics:

- DC01 System Linearity: Depending on the specific way product production relations are modelled, including production design questions can either introduce significant nonlinearities or be mostly linear. The former is the case when specific technological models like geometry dependent tool path models are considered, while the latter is the case if the effect of a finite number of considered product variants is fully parametrised.
- DC02 Number of Decision Variables: Depending on the specific type of inclusion product design consideration can range from a moderate to a large increase in the number of decision variables.
- DC03 System Expertise: Including product design may especially improve long-term development expertise, as well as the consideration of specific market demands.
- DC08 Perspective Diversity: The perspective of product designers is typically very different from production. Design functions follow a very different objective structure and typically consider very different systems. Thus, the perspective diversity increases significantly, with the inclusion of product design.
- DC11 Data Acquisition Intensity: While data on existing product features is typically available in companies, information on the effects of product design on production processes is based on estimation and thus acquired manually. Therefore, including product design leads to large increases in data acquisition intensity.
- DC12 Time Horizon: Decisions on product design are typically medium to long-term. Overall, a longer time horizon may be required especially for shorter decisions.

Variants:

- Configured products: When products are entirely described by configurators, at least in principle, a full formalisation of all variants and their effects on production is possible. To predict production capacities for example, statistical probabilities of products can be used.

- Engineer-to-order business: In engineer-to-order businesses, every product or order is designed before production. Thus, a close interaction of production and product design is obligatory.
- Design-free production: Some organisations offer the production of goods without any own design capabilities, entirely based on product specification provided by customers. This requires an ability to translate the product specifications into production capabilities within short time. This translation function needs to be represented in some capacity in PNC models.

Quality Management & Control

Quality management and control describes all activities concerned with ensuring the quality and safety of products sold by the organisation. Important processes are the qualification of new products and processes, consideration and investigation of any quality or safety concerns, both preventative and diagnostic, and the continuous monitoring of product and process quality. In PNC tasks, quality management and control are particularly important if technological capabilities are considered in detail and if there are heterogeneous market demands in terms of product quality. Furthermore ramp-up processes of new products and new technologies can be quality sensitive.

Modelling Characteristics:

- DC01 System Linearity: Quality related issues can be modelled stochastically. If for example the defect rate can be estimated per product, resource, and time after introduction, a parametrised linear model is sufficient. If complex learning processes play a significant role, the linearity decreases.
- DC02 Number of Decision Variables: Usually the inclusion of quality management and control has only a small impact on the number of decision variables, as the number of available quality related interventions is low compared to other decision types in PNC tasks.
- DC03 System Expertise: Including the expertise of quality management and control moderately increases the expertise of the DMC particularly if the introduction of new technologies or products is concerned or if defect rates are subject to change.
- DC08 Perspective Diversity: The perspective of quality management and control usually differs significantly from production management. Though the considered

system overlaps, the relevant objectives are disparate. Thus, the inclusion leads to a moderate increase in perspective diversity.

- DC11 Data Acquisition Intensity: Data on quality related aspects of production are often managed in specific IS. Also, data on product quality may not be available in sufficient granularity. Lastly, several quality related aspects require expert estimation, like forecasted defect rates for new products. Thus, the inclusion moderately increases data acquisition intensity.
- DC12 Time Horizon: Decisions on product quality are usually short to medium term. They are thus unlikely to affect the time horizon.

Site & Resource Management

Site and resource management is concerned with provision, management, and maintenance of the necessary infrastructure and resources for production. This includes building construction and management, management of energy, water, and heat, ecological, security and safety management, and plant and fixture construction and maintenance. In PNC tasks, site and resource management may for example support with site construction, layout planning, attribution of indirect costs and estimation of change times and costs.

Modelling Characteristics:

- DC01 System Linearity: Most aspects of site management can be modelled linearly, such as maintenance efforts, costs of space, or resource consumption. However, especially space requirements are non-linear thus decreasing linearity when modelled accurately.
- DC02 Number of Decision Variables: As the number of decisions in site and resource management typically scale with the amount of production equipment, which is often lower than the number of distinct orders, the inclusion of site and resource management has a moderate effect on the number of decision variables.
- DC03 System Expertise: Including site and resource management may help to better understand the effect, changes in configuration have on indirect costs and indirect effects on other objectives. Thus, it can significantly increase the system expertise.
- DC08 Perspective Diversity: Even though site and resource management are usually relatively well aligned with production in terms of considered system and

objectives, as each site has a unique instance of this domain, the inclusion increases perspective diversity moderately.

- DC11 Data Acquisition Intensity: Usually, data on the existing costs of site management are available. The attribution of the necessary efforts to the processes causing or demanding them is often less well documented. Furthermore, modelling changes requires an estimation of the effect on efforts that is very difficult to capture in data. Thus, a comprehensive inclusion of site and resource management moderately to significantly increases data acquisition intensity.
- DC12 Time Horizon: Decision in site and resource management tend to be more long-term but generally align well with PNC time horizons.

Variants:

- External site management: When organisations operate within industry parks or have outsourced parts of the site and resource management, data acquisition typically becomes more difficult, and the number of available decisions may be reduced. However, some aspects could be simpler to model as efforts are contractually agreed upon.
- Immovable assets: In some industries, such as chemical, steel production, or metal casting, production equipment is almost immovable or at least very difficult to relocate. In that case, the inclusion of site and resource management is more focused on equipment changes as well as resource management.

Human Resource Management

Human resource management is responsible for the attraction, selection, and acquisition of new personnel, development and training of the existing workforce and managing employee retirements and lay off. Within this scope human resource management ensures the personnel has the right capabilities and is available in the right number while also considering demographic developments. In PNC decisions, human resource management may decide on the hiring policies, retraining offers, and retirement policies. The specific scope of action of human resource management is very dependent on the particular country, its regulation as well as degree of unionisation and their leverage.

Modelling Characteristics:

- DC01 System Linearity: Some aspects of human resources can be modelled accurately in linear fashion, the attractiveness of job offers, voluntary trainings, and early retirement offers are non-linear. Thus, a comprehensive inclusion of human resource management can significantly decrease linearity.

- DC02 Number of Decision Variables: The number of distinct decisions of human resource management modelled in PNC decision is limited, thus the effect on the number of decision variables is relatively minor.
- DC03 System Expertise: Including human resource management may significantly increase the understanding of the demographic and ability-related development of the workforce. Furthermore, it may provide a better understanding of the available workforce flexibility.
- DC08 Perspective Diversity: Human resource management may bring significant additional knowledge to the specific abilities of local personnel and its effect on the dynamic capability development of different sites.
- DC11 Data Acquisition Intensity: Data on the age and planned retirement ages of employees as well as salaries are usually available in companies, but subject to strict privacy regulations. Data on capabilities and capability development is usually less formalised outside of formal operator licences and requires significant effort in data acquisition. Overall, the inclusion of human resource management can moderately increase data acquisition intensity.
- DC12 Time Horizon: The time horizons of human resource management are generally well aligned with PNC decisions.

Variants:

- Large leasing workforce: Some organisations rely on a large share of leased workers. This usually results in higher flexibility but lower capability levels. In this case, PNC decisions are less inhibited by human resource management. Data on the personnel may be more formalised, but only available as far as is contractually agreed.
- Strict worker protection laws/agreements: In some countries, operation-related layoffs are strictly limited or contracts with worker unions inhibit organisation's ability to scale the workforce flexibly. In this case the details of such laws or contracts need to be considered in the modelling. PNC decisions than require a more holistic view, as personnel may only be shifted between tasks instead of full reductions.

Strategic Management

Strategic Management is concerned with making fundamental decisions on the organisations long term direction, addressed markets, competitive strategy, outside relations and inside foci. It may be organised within the organisations business units. In summary, strategic management has the most holistic view of the organisation encouraging a comprehensive consideration of objectives and domains. Decisions in strategic management also tend to be more deliberative and not as strictly defined.

Modelling Characteristics:

- DC01 System Linearity: The inclusion of strategic management encourages the consideration of more non-linear, qualitative objectives thus decreasing linearity.
- DC02 Number of Decision Variables: Strategic decisions are often more abstract and less concerned with small details. However, they require a broader consideration of scenarios and have a larger system scope. Thus, the inclusion of strategic management is neutral or moderately increases the number of decision variables.
- DC03 System Expertise: The inclusion of strategic management ensures a broad comprehensive consideration of the entire organisation and its environment. However, the knowledge on detailed processes and connections may be limited. Overall, the system expertise is increased.
- DC08 Perspective Diversity: Strategic management unifies several functions of an organisation. Thus, it usually significantly increases perspective diversity.
- DC11 Data Acquisition Intensity: Strategic management is often concerned with the interaction between the organisation's actions and its environment. Thus, decisions involving strategic management need to consider a broad range of external data. However, the broad, long-term focus of the decisions may alleviate the need for very detailed data acquisition.
- DC12 Time Horizon: The time horizons strategic management decisions are usually long, increasing the time horizon. However, strategic management may sometimes also require very swift, unscheduled decisions.

A2.5 PNC Element Library

In the following the principal decisions and corresponding elements of PNC tasks are discussed. These consist of configurative decisions, where changes to different types of resources are made and allocative decisions, where resources are assigned to each other or production volumes are allocated at a resource. In Table A 6, the relevant resources and their change modes are defined, as well as an estimation of the time range it takes to execute them. These time ranges are dependent on the specific resources. Depending on the type of PNC task, different changes may be considered. The time horizon of any decision should be chosen such that the changes can take effect, i.e. the time horizon should be around two times the duration of the longest change mode. The here presented set makes up the majority of decisions in PNC tasks. When additional domains are considered or in specific situations, additional decisions may be included.

Table A 6: PNC Element Library and Main Change Mode

PNC Element	Description	Change Mode	Estimated Time range
Production Site	Sites with value-adding activities operated by the focal company	Set-Up	2-5 Years
		Expand	1-3 Years
		Consolidate	1-3 Years
Auxiliary Site	Sites which accommodate non-value adding functions of an organisation such as, service, sales, development, etc.	Set-Up	3-24 Months
		Consolidate	3-18 Months
Logistic Site	Sites which are specifically used for logistic purposes such as warehousing, trans-shipment, or distribution. They require significant invest and space but often operate with relatively few low skilled personnel.	Set-Up	1-5 Years
		Consolidate	1-2 Years
Supplier	Supplier for parts, resources, and processing.	Select	1-12 Months
		Develop	3-24 Months
Production Technology	Type of processing characterised by a specific set of necessary expertise and characteristics	Set-Up	0.5-5 Years
		Move	0.3-3 Years
		Consolidate	3-12 Months
Production Equipment	Machines, lines, and plants which are instantiations of a production technology.	Set-Up	1-24 Months
		Move	3-12 Months
		Adapt	0-6 Months
		Consolidate	1-12 Months
Auxiliary Capability	Capabilities associated with not directly value-creating functions like service, sales, or development	Establish	0.5-3 Years
		Consolidate	6-18 Months
Personnel	Staff directly or indirectly associated with value creation, process expertise	Hire	1-24 Months
		Retraining	1-12 Months
		Lay Off	0-3 Years
Tool	Production technology and product specific appliances used to customise production resources to products	Create	0.5-12 Months
		Move	0-3 Months
		Discard	0-3 Months
Transport Mode	Type of transport chosen on a specific route	Set-Up	1-12 Months
		Cancel	1-6 Months
Releases & Certifications	Allowances to produce products on specific resources	Acquire	1-12 Months
Work Time Model	Policy by which worker capacity is determined temporarily	Change	0.5-12 Months
Set-Up	Configuration of resources determining capabilities and processing characteristics	Change	0-1 Week

In the following sections, the PNC elements and corresponding change modes are discussed. In addition, typical production volume groupings and corresponding allocation decisions are defined.

Production Site

Site at which value adding activities that alter the products are performed, which is owned or at least operated by the organisation. The site includes an area of land, a build infrastructure, and connection to energy, water, and other supplies, transportation connections. At a site, production technologies with corresponding resources are present, as well as tools used in the production processes. Typically, a set of personnel, either directly or indirectly employed at the organisation is associated with a site. These employees may conduct value adding processes in which case they are associated with a set of resources they work on, or provide auxiliary capabilities, which may be located at the site.

Production Site Set-Up:
Describes the establishment of a new site including land purchase, construction, and commissioning of a site. The duration depends among other things on the local regulatory conditions, availability of planning and construction services, the size of the planned site, the building requirements of the organisation, and the technologies that the site is supposed to host. Sometimes existing infrastructure can be acquired which can significantly reduce set-up times.

Production Site Expansion:
Describes the major alteration of infrastructure at an existing site to expand its production capacity. This typically includes the construction of new buildings. The duration is determined by similar factors as the set-up but may also be affected by the complexity of and necessary alteration to the existing infrastructure. In cases where the expansion has been prepared in previous building steps, it can be accelerated significantly.

Production Site Consolidation:
Describes the sale or closure of a production site. Depending on the type of consolidation, this may include the shipping or dismantling of resources, deconstruction of buildings, restoration of environmental conditions and operational layoffs. Thus, the time depends on the type of consolidation, local regulations, size of the site, and production technologies present.

Auxiliary Site

Site operated by the organisation at which no value-adding or logistical processes are conducted. These sites typically host sales and service functions, but may also be dedicated to product development, or organisational management. As auxiliary sites often do not require specialised infrastructure, they are quicker to set-up and consolidate.

Auxiliary sites are not often considered in PNC tasks but may be important when customer proximity is critical.

Auxiliary Site Set-Up:
Describes the establishment of a new auxiliary site including land purchase, construction, and commissioning of a site. The duration depends among other things on the local regulatory conditions, availability of planning and construction services or existing infrastructure, the size of the planned site, and the auxiliary functions to be allocated.

Auxiliary Site Consolidation:
Describes the sale or closure of an auxiliary site. Depending on the type of consolidation, this may include the deconstruction of buildings and operational layoffs. Thus, the time depends on the type of consolidation, local regulations, and size of the site.

Logistic Site

Site operated by the organisation that hosts logistic processes, i.e. product and component storage, packaging, and transshipment. These sites typically consist of large buildings and have a good connection to different transportation modes. Depending on the chosen degree of automation, the products handled, the volume of handled products, they may require significant investment.

Logistic Site Set-Up:
Describes the establishment of a new logistic site including land purchase, construction, and commissioning of a site. The duration depends among other things on the local regulatory conditions, availability of planning and construction services or existing infrastructure, the size of the planned site, and the chosen automation.

Logistic Site Consolidation:
Describes the sale or closure of a logistic site. Depending on the type of consolidation, this may include the deconstruction of buildings, dismantling or shipment of logistic infrastructure and operational layoffs. Thus, the time depends on the type of consolidation, local regulations, the degree of automation and size of the site.

Supplier

Another organisation that has an established connection with the focal organisation and regularly provides it with goods, production resources or services. In production supply chains, suppliers have their own sites, technologies, resources, and personnel. They are chosen by the organisation based on capabilities and capacities, as well as possible interaction with the organisation's own sites. Suppliers may have different levels of integration or coordination with the organisation.

Supplier Selection:
Describes the selection of the supplier for specific production volumes and possibly the establishment of an ongoing relation between the organisation and the supplier. The execution time depends on the existing relation, the complexity and volume of the production processes, the existing free capabilities and capacities of the supplier, the desired level of integration and coordination, and the proximity of the organisation.

Supplier Development:
Describes the development of a supplier to satisfy the desired capabilities of the organisation. This may include the purchase and provision of tools and resources, the improvement of processes, or the design of processes and products. The duration depends on the type of development, the complexity and volume of the processes, the physical and cultural proximity to the supplier, and the existing relationship.

Production Technology

A general technology used to increase the value of a product. Production technologies are classified according to DIN 8580 and VDI 2860. Using production technology requires the knowledge of the general process, dependencies between process parameters and its results in terms of product quality and production efficiency, and knowledge of equipment used in this technology. Depending on the specific technology the required equipment and specialisation varies. Technologies may also be mastered to varying degrees.

Production Technology Set-Up:
Describes the introduction of a technology at an organisation. The necessary time required depends on the existing knowledge base, access to external knowledge, and the complexity of the technology. In some cases, it may be possible to acquire knowledge through the takeover of other organisations.

Production Technology Move:
Describes the replication of a technology that is already present in the organisation either as a replacement or addition. The execution times depend on the local knowledge base, availability of trained personnel, the possibility to relocate personnel, and the complexity of the technology.

Production Technology Consolidation:
Describes the consolidation of all activities concerned with a particular technology. This often involves personnel reorganisations. The execution time depends on the associated functions and personnel and local regulations.

Production Resources

A resource necessary to for a specific set of production process, typically a station, machine, line, or plant. A resource is associated with a particular production technology or a set of technologies and operated by a set of employees. Production resources may be used for multiple different products and production processes. The operation of resources typically requires specific knowledge in addition to technology specific knowledge. Production resources are typically equipped with specialised tools, which adapt them to particular processes or products.

Production Resource Set-Up:
Describes the acquisition, construction, and commission of a production resource. The execution time depends on the organisational knowledge, the complexity of the resource and its associated processes, availability of construction space, and the availability of the resource for purchase.

Production Resource Move:
Describes the relocation of a resource either within a site or to another site. Execution times depend on the complexity of the resource and the necessary changes to it, the transportation time between sites, the necessary bridging volumes, knowledge available at the new site, and available construction space.

Production Resource Adaption:
Describes the change of a production resource to adhere to new requirements, for example to produce new product variants, be more efficient, or comply with new safety, environmental, or quality regulations. The execution times depend on the type of change and the resource, its ability to suspend operation, and complexity. Furthermore, available knowledge, necessary bridging volumes, and the integration with the rest of the production system play a role.

Production Resource Consolidation:
Describes the consolidation of a production resource either as a sale or a deconstruction. Execution times depend on the complexity of the resource, the availability of necessary personnel, and the type of consolidation chosen.

Auxiliary Capability

A not directly value-creating function at a production site, such as sales, development and design, or procurement. Involves the creation of suitable organisational structures, the acquisition, repurposing or creation of necessary infrastructure, and the hiring or relocation of necessary personnel.

Auxiliary Capability Establishment:
Describes the creation of an auxiliary capability at a site. Execution time depends on the number of required employees, the availability of skilled personnel, the availability of necessary infrastructure, and the complexity of the required organisational integration.

Production Resource Consolidation:
Describes the consolidation of an auxiliary capability at a specific site. The capability is either mover to another location or abandoned entirely. Execution time depends on the local regulations, the complexity of the organisational disintegration, and the type of consolidation.

Personnel

Staff that is either directly responsible for value adding processes, involved in indirect support processes or other functions such as sales, service, procurement, or development. Important aspects of personnel are the qualifications employees have as well as their age. Those factors, as well as the likelihood employees will quit and the protections against operational layoffs are determined by the location. Usually, organisations also employ a leasing workforce, typically in roles with lower qualification requirements and higher flexibility. PNC tasks are usually not concerned with individual employees but with the body of employees and its changes.

Personnel Hiring:
Describes the acquisition of suitable personnel for a task. The achievable hiring rate depends on the organisations size, the availability of personnel at the location, the general qualification level in the region, the complexity of the tasks, and the organisations willingness to accept hiring costs.

Personnel Retraining:
Describes the qualification of the existing workforce for new tasks. The retraining duration depends on the existing qualification of the workforce, the complexity of the new task, the organisations training capacity and capability, and the demographic composition of the personnel.

Personnel Layoffs:
Describes the layoff of no longer required personnel, either by leasing workforce adjustment, direct layoffs, retirements, or contract dissolution settlements. The achievable personnel reduction rate depends on the type of layoff, the local regulations, and the demographic composition of the workforce.

Tools

Equipment used in production resources used to perform the production processes. Usually adapted to the specific process or product and subject to wear. Depending on the technology tools vary in specificity, costs, and IP relevance. Tools can be created by the organisation itself or sources from suppliers.

Tool Creation:
Describes the creation of new tools. Execution time depends on the knowledge of process and product, the complexity of the technology, the type of tool, the availability of tool production capacity, and necessary transportation times.

Tool Moving:
Describes the relocation of tools from a production resource to another, either at the same site or another or even to a supplier. Execution time depends on the complexity and specificity of the tool and necessary transport times.

Tool Discarding:
Describes the discarding of tools either in a sale or as waste disposal. Execution time is usually only an issue for very large tools or tools that are IP critical.

Transport Mode

Transportation route and set of modes used to fulfil a transportation demand. Typical modes include truck, sea freight, dedicated air freight, belly freight, and train. Routes can be operated by the organisation itself or one or multiple operators. Routes may operate on scheduled frequency or based on demand. The availability of different routes depends on the logistic capacities and capabilities of the organisation, the origin and destination of the freight, suitable infrastructure on the route, and its size and characteristics.

Transportation Mode Set-Up:
Describes set-up of a new transport connection. The execution time depends on the specificity of the transportation demand, the availability of providers or own capacity, and the existence of suitable infrastructure.

Transportation Mode Cancelation:
Describes the cancelation of a transportation contract or repurposing of transportation capacity. Execution time depends on contractual agreements.

Releases and Certification

Customer specific releases or certifications issued by governments or third parties allowing the production of products on specific resources, at specific locations with specific personnel and processes. Depending on the type of release or certification the requirements can differ significantly.

Release and Certification Acquisition:
Describes fulfilling the requirements specified by a customer or certification agency and passing corresponding checks. Execution times depends heavily on the type of release or certification, the complexity of the process, risks arising from it, and particular requirements of customers or agencies.

Work Time Model

Specific policy by which employees at a specific production resource are assigned to working times. Determines the achievable production capacity at a resource. Work time models are typically chosen based on the ratio of capital and wage costs of a production process. Additionally, local regulations, personnel availability, and the connection to other production processes may be a factor.

Work Time Model Change:
Describes the change of the work time model for a specific production resource. Execution time depends on the flexibility and availability of personnel, local regulations, and the necessity for and complexity of buffer storage to other production processes.

Set Up

The specific setting a production process is conducted by on a particular production resource, especially considering the allocation of active tools. For most PNC tasks individual set up processes are irrelevant due to the very short required time, but some set-up changes require up to a week.

Set Up Change:
Describes the change of production resource set up. Execution time depends on the availability of skilled personnel, the type of set up change required, and the complexity of the particular production resource.

Production Volume Allocation

Required production volumes can be allocated to resources in different sets. In the following typical instances of allocations are discussed. In some cases, multiple of these distinctions can be combined. Which type of allocation is most appropriate depends on the type of network structure and typical organisational set up as well as the importance different technologies and markets. These allocations can occur on a site level, or on a production resource level. On both levels, production may also be allocated at a supplier. For all cases, the allocation decision is significantly quicker to execute than the configurational decisions corresponding to them.

Product Family
Describes the allocation of an entire product family consisting of multiple different variants. This typically also includes the responsibility for process development, sourcing, and sometimes sales.

Product Variant
Describes the allocation of a specific product variant to a site or production resource. Usually only allows for minor adjustments, for example due to different local factors.

Production Technology Group
Describes the allocation of a specific group of production processes grouped by similar technologies, often across product families. This is usually also associated with responsibility for those technologies and their development.

Production Process
Describes the allocation of a specific production process, typically within a product family.

Regional Production Volume
Describes the allocation of production volumes demanded by a particular region, usually across multiple production processes.

Production Volume
Describes the allocation of a specific production volume irrespective of qualitative delimitations.

Production Order
Describes the allocation of a specific production order consisting of a set of products send to a specific customer.

A2.6 External Influences

In the following, the influences on PNC tasks are outlined. They are structured according to the types of influences on global production, as defined by Lanza et al. (2019). For each type, several relevant aspects are introduced. A characterisation of situations where these aspects are particularly relevant, which objectives they primarily affect, and how volatile they are, accompanies a general description of them. Table A 7 provides an overview of the relevant aspects.

Table A 7 External Influences on PNC Tasks Based on Lanza et al. (2019)

Influence Category	Aspects
Market & Market Development	Customer composition, customer preferences, economically driven demand, competition.
Cost Factors	Local costs of labour, capital, material, energy, and communication, local productivity.
Logistics	Supply availability, transportation and inventory costs, transport lead time
People & Culture	Training levels, employee turnover rate, cultural preferences
Legal Factors	Rule of law, knowledge protection, corruption
Political & Governmental Factors	Political stability, subsidies, currency, duties

Market & Market Development

Describes the set of potential customers, competitors, and the relation between them. Depending on the constitution of the existing markets different aspects may have to be considered. For many organisations, markets are the primary cause of volatility, as changes in order volumes can disproportionally affect profitability and because large and sudden shifts in markets are common. In the following some of the important considerations and causes for market side volatility in PNC tasks are described.

Customer Composition

The number and type of customer may change quickly if a product is introduced to new markets, affected by technological disruption or subject to fashion cycles. This is particularly relevant for non-commodity products. Changes in this section can be large and difficult to predict.

Customer Preferences

The preferences by which customers chose products may shift over time. For example, whereas delivery speed may be a primary differentiation factor when a product type is newly introduced, price may become more important when the market is saturated. This may be particularly relevant for more expensive products with deliberate purchasing decisions. Changes in this aspect tend to be relatively slow.

Economically Driven Demand

The purchasing power or spending or investing wiliness of customers may change with the generally economic conditions. This can in part be compensated by adjusted pricing. This should typically primarily affect non-essential goods and deferable investments. Changes in this section typically occur with a medium speed and tend to be somewhat cyclic.

Competition
The state and condition of competitive organisations in a market is subject to both slow shifts caused by the organisations strategies or changing environmental conditions and rapid developments due to disruptive market entries. This type of change is particularly relevant in products with high degrees of governmental intervention, outdated technological standards or limited defensibility. Changes in this section can be very large and happen moderately quickly.

Cost Factors

Cost factors describe the boundary conditions for production at a specific location. Changes in cost factors can completely alter the competitiveness of a site especially if the organisation competes with others around the world who experience different changes in their cost factors.

Labour Costs
The average costs of worktime at a location. Labour costs vary across countries and regions. Additionally, they differ across occupations and education levels. Labour costs are particularly relevant for organisation with a large share of manual labour. Furthermore, organisations who sell a majority of their products outside the markets they produce in are affected. Changes in labour costs occur relatively slowly and are usually predictable.

Capital Costs
The costs of burrowing at a specific location, usually with the intention to finance investments in infrastructure, equipment, or material. Capital costs can differ moderately from one country to another. Organisations are typically able to avoid very unfavourable conditions through their global network, but some degree of localised financing is usually necessary. Capital costs particularly affect organisations with ongoing expansions, a large share of equipment-related costs and organisations with long lead times that need to finance material and production. Changes in capital costs usually occur with a moderate speed.

Material Costs
The costs of material necessary for production, including raw materials, consumables, and components. Material costs differ significantly across regions, depending on the specific material. Changes in material costs particularly affect organisations with large shares of material costs. Material costs underlie slow shifts but are also affected by sudden changes, particularly raw material.

Energy Costs
The costs of energy necessary for production, typically in the form of coal, gas, heat, and electricity. Energy costs differ significantly across regions. This particularly affects organisations that process raw materials or otherwise consume a lot of energy. Energy costs are subject to short term fluctuations, but the overall energy costs only change with moderate speed.

Communication Costs
The costs of communicating within and between factories. Today these costs are dominated by the costs of data storage and computing infrastructure. Though there are local differences caused by underdeveloped infrastructure or particularly open access to server infrastructure. This particularly affects organisations with high degrees of automation and large data requirements. Changes in communication costs occur relatively slowly.

Productivity
Describes the ratio between economic value created and resources consumed. This is largely determined by the production system the organisation employs, as well as local education levels and work times. This affects all kinds of organisations. However, shifts occur relatively slowly.

Logistics

Describes the conditions and system responsible for the timely transportation and storage of products. By extension, the broader supply chain providing components can also be considered as part of this influencing factor. Changes in the logistics system happen both suddenly as disruptions and over long-time spans as shifts. Generally, organisations with very time-sensitive processes are more prone to experience large effects of logistic volatility.

Supply Availability
The availability of necessary materials, components, and services. Missing parts or materials can severely hamper production and even items with a miniscule value share can cause production outages and consequently losses. The availability of local supply is affected by natural catastrophes, production disruptions of suppliers, strikes, delivery disruptions, financial difficulties of suppliers, and dynamic industry capacity in the short term. Long-term, the development of local industry and society, and governmental decisions also impact supply availability. This influence is particularly important for

organisations that have minimal buffer storage or require supplier specific goods, which cannot easily be replaced. Supply availability can change quickly with large effects.

Transportation Costs
The direct costs of transporting items from one place to another. Include the costs incurred during the transport and packaging of goods. These costs change slowly due to technological and economic developments but can also be affected by political factors. Changes in transport infrastructure can also lead to quick shifts in transportation costs. These costs are particularly significant for products with significant shipping costs, typically those with low value density. Overall transportation costs change relatively slowly and can be planned accordingly.

Inventory Costs
Costs of holding inventory, excluding capital costs. These costs are driven by the availability of local inventory and thus change slowly with economic developments and infrastructure development. These costs are particularly impactful for organisations producing or consuming bulky items or requiring large storage quantities. Changes are relatively slow.

Transport Lead Time
The average time necessary to transport items between two places. This is affected by local infrastructure, the selected transport mode, and the frequency with which routes are served. Furthermore, necessary transshipment processes can affect the lead times. This is particularly important for organisation that either use lead times as a differentiation factor or with very time-sensitive processes. Changes can occur moderately quickly due to economic changes or changes in infrastructure.

People & Culture

Aspects associated with the society and individuals at a location. These aspects are typically more difficult to define. They are visible when considering larger aggregates of a population. These aspects affect organisations with different cultural backgrounds and orientations differently. Changes in these aspects are typically relatively slow.

Training Levels
Degree to which employees are educated and trained for occupations the organisation offers. This aspect depends on the local education and training system, as well as the formation of local clusters. This aspect particularly affects organisations that require specific knowledge from their personnel. Changes in training levels happen relatively slowly.

Employee Turnover Rate
Degree to which organisation switching is common in a society. This may be associated with the ability of organisations to lay off personnel due to operational reasons. The turnover rate affects the ability to protect and sustain knowledge and the flexibility of the workforce. This particularly affects organisations who require high levels of training, and which use proprietary knowledge as a competitive advantage. Changes in employee turnover are slow.

Cultural Preferences
Describes preferred behaviour of individuals within groups. Examples are the tendency to strictly follow orders, the importance of relationships, or the directness of expression. This affects all organisations operating across multiple cultural spaces. Changes in these preferences are slow and the effect on PNC decisions is limited.

Legal Factors

Aspects associated with the degree to which organisations can rely on the rules of law to apply and protect them. Insufficient protections may be a breaking point for the engagement of an organisation in a country. Changes to legal factors typically occur relatively slowly.

Rule of Law
The degree to which existing laws actually apply in the organisation of daily business. This varies across countries and can change particularly when political changes occur. For companies, it is important to be able to rely on the enforcement of laws, so that business processes can be planned accordingly. Changes in the rule of law occur relatively slowly.

Knowledge Protection
Degree to which the protection of IP is valued and enforced. Missing IP protection can lead to the degradation of IP as a competitive advantage and threaten the viability of organisation business models. Weak IP protection can be the result of government inability or politically designed to strengthen local organisations. This primarily affects organisations who rely on IP as a technological advantage in terms of their products or processes. Changes in knowledge protection occur relatively slowly.

Corruption
Degree to which corruption is common at a location. High levels of corruption effectively preclude organisations from engaging at that location, as they would have to violate their policies to do so. This affects all organisation committed to a code of conduct

against corruption. Corruption levels can change due to the deterioration of state power or political changes. These changes often occur slowly but can also happen suddenly.

Political & Governmental Factors

Aspects describing the interaction of local politics with organisations. These aspects often directly influence the profitability of PNC decisions. Thes aspects particularly affect organisations operating in multiple political spheres or which rely on governmental subsidies. Changes in political factors can occur moderately quickly.

Political Stability
Degree to which a local political system is stable over time. Low political stability can be risky for organisations, as the conditions for their business may be upended quickly. This particularly affects organisations that engage in countries with marginal political stability. Changes in political stability can occur moderately quickly or surprisingly, but most of the time slow shifts are observable.

Subsidies
Regulations that economically aid the business model of organisations through specific loans, product discounts, tax exemptions or others. Can apply to specific organisations or entire industries. Subsidies can be a deciding factor in PNC decisions. Subsidies can change moderately quickly depending on the political stability and underlying law and governmental system.

Regulation
Non-economic regulations for worker safety and protection, environmental protections, customer safety, corporate responsibility, dual use restrictions, risk management, or others. These regulations can affect the viability of business models and lead to increased costs or complexity. Regulations may also protect certain markets and provide a competitive advantage. This affects organisations in heavily regulated industries the most. Changes in regulations can occur moderately quickly depending on the political stability and underlying law and governmental system.

Currency
Currency used at relevant locations, i.e. places where material and goods are sourced, production sites, and markets. Changes in currency rates between these places can alter the cost and profit structure drastically. Currency fluctuation can occur based on local inflation, or in economic or political shifts. This affects organisations that operate across the borders of currency blocks the most. Changes in currency rates can occur

quickly and drastically depending on the stability of the considered set of currency regions.

Duties
Tariffs or duties paid for products or services entering a market from the outside. Duties are typically set by the type of good and differ between considered pairs of countries. They particularly affect organisations with imbalanced localisation of value-creation and value-capture. Duties can remain very stable for long periods but may suddenly change, typically for geopolitical reasons.

A2.7 Decision Process Characteristics

In the following a schema to capture the process characteristics is provided. It consists of: (i) defining the nominal or typical process using BPMN, (ii) identifying roles and responsibilities in the process using RAM, and (iii) specifying additional characteristics.

Process Definition

The decision process is captured using BPMN. For complex decision processes that involve multiple different organisational functions, swim lanes indicating the responsibility for actions can be used.

Role and Responsibility Identification

To assign roles and responsibilities, the RAM can be used. It associates the individual actions with five distinct responsibilities (Cabanillas, & Resinas et al., 2018, p. 554):

- Responsible (R): Person required to perform the activity until completion and if applicable approval by the accountable person. Typically, only one per activity.
- Accountable (A): Person required to approve or disapprove the activity performed by the responsible person. Becomes accountable for the results of the activity after approval. Typically, only one per activity.
- Support (S): Person who may assist the responsible person in performing the activity. The responsible person may delegate work to this person.
- Consulted (C): Person who passively assist the completion of the activity by providing guidance or opinions when asked.
- Informed (I): Person who is informed about the progress of the activity and its results.

To connect RAM to the process model, each task is captured as one activity. Responsibilities are associated with a set of roles that are defined as well. These roles are typically aligned with functional roles within the organisation.

Additional Characteristics Specification

Using the BPM and RAM of the decision process a few additional characteristics can be deduced. These include the formalisation of the process, the termination type, and the occasion for decision. Additionally, the decision time and frequency may also be derived from the previously described modelling.

Formalisation
The degree to which a decision is formally specified within the organisation. The dimensions of formalisation include the roles in the DMC, the inputs and outputs of the decision process, the sequence within the process, the decision-making rules, and the occasion for decision making.

Termination Type
Different types of termination can be distinguished:

- *Linear processes* follow a linear structure without planned iterations. The process is only repeated if circumstances have drastically changed, or process errors occurred. These processes are likely more quantitative, have high levels of decision routine and relatively low requirements for explainability.
- *Iterative processes* feature a planned iteration before the ultimate decision is made. They are only concluded when the decision process has satisfied the desire of the DMC to consider different options, influences, and relationships. These processes may coincide with an increased desire for explainability. They likely also require a more comprehensive consideration of the system, its environment, and different objectives.
- *Monitoring processes* continuously iterate a decision-making process, but only select a decision, if predetermined criteria, which warrant a reaction are met. In contrast to iterative processes, the satisfaction criterion is not perceived coverage of the decision space but the transgression of predetermined result thresholds.

Decision Occasion
Multiple different occasions for the decision process can be differentiated:

- Management demand can require a *subjectively triggered* decision-process. In this case the frequency of the process is not plannable.

- External events may be a trigger for *rule-based triggered* decision processes.
- Preceding decision processes can cause a decision process as part of a *hierarchical schedule*.
- *Rolling planning schedules* decision processes in regular intervals and can thus be prepared accordingly.

A2.8 Method Library

In the following the method library used in this work is described. It utilises the methods introduced in Appendix A1. To minimise the necessary iterations, the methods should be chosen in the following order: (i) predictive methods, (ii) configurative methods, (iii) prescriptive methods, (iv) decision selection methods, (v) scenario generation methods, and (vi) meta models. In the following, selection criteria for each, that correspond to the decision situation and the other selected methods are presented. These criteria serve as a basis for selection. However, they cannot be viewed as an automatism, model developers still have to consider carefully which method composition makes sense for their application.

Predictive Methods

The choice of predictive methods is primarily governed by the system under consideration and the pursued objectives. In general, the simplest model that represents the system with acceptable accuracy should be chosen, as it allows for faster calculations and is more suitable for prescriptive decision-making. In many cases it is worthwhile to consider using multiple predictive methods to represent different system aspects. Table A 8 displays the selection criteria for the different available predictive methods.

Table A 8: Selection Criteria for Predictive Methods

Category	Method	Selection Criteria
Deterministic Models	Linear Models	• System behaves in linear and continuous fashion • Number of decision variables is very high • Desired AC is very high • Decision time is very short
	Mixed Integer Linear Models	• System behaves mostly linearly with discrete variables • Number of decision variables is very high • Desired AC is very high • Decision time is short
	Quadratic Models	• System is captured well using quadratic functions • Number of decision variables is moderately high • Desired AC is high
Simulation	Discrete Event Simulation	• System changes in discrete steps and complex temporal processes are considered • Uncertainty is high • Number of decision variables is limited
	Agent-Based Simulation	• System contains multiple agents that act independently • Number of decision variables is limited
	System Dynamics	• System behaves in complex but continuous fashion, captured well by differential equations • Number of decision variables is limited
Stochastic Models		• System behaves mostly linearly • Uncertainty is high • Number of decision variables is moderately high • Desired AC is high

Configurative Methods

Choosing configurative methods requires a consideration of the desired decision-making process, the structure of the decision space and the desired AC. When partially prescriptive models are desired the analysis of usage criteria should be conducted for the predictive and prescriptive decision variables separately. In contrast to the predictive methods, where only the characteristics of the decision situation influence the choice of methods, configurative methods can also be influenced by the chosen predictive method. Table A 9 shows the assessment of usage criteria and dependencies on other methods.

Table A 9: Selection Criteria for Configurative Methods

Category	Method	Selection Criteria	Dependencies
Creativity Techniques	Idea Generation	• Decision is made or prepared in groups • Decision space is relatively unstructured • Desired AC is low • Number of decision variables is low • Decision time is long	
	Systematic Alternative Construction	• Decision space is at least roughly structured • Feasible decision space is sparsely populated • Desired AC is moderately low • Number of decision variables is moderately low • Decision time is moderately long	
	Distributed Expert Mining	• Perspective diversity is high • Desired AC is moderately low • Number of decision variables is moderately low • Decision time is long	
Design of Experiments		• System linearity is low • Uncertainty is high • Decision space is structured • Number of decision variables is moderately high • Decision time is moderately long	
Constraint & Objective Variation	Parameter & Sensitivity Exploration	• Uncertainty is high • Decision space is structured • Desired explainability is high • Number of decision variables is moderately low • Decision time is moderately long • Adequate computing capability is given	
	Pareto Front Exploration	• Perspective diversity is moderately high • Desired AC is moderately high • Uncertainty is moderately high • Decision space is structured • Desired explainability is high • Number of decision variables is moderately high • Decision time is moderately long • Adequate computing capability is given	
	Constraint Relaxation	• Uncertainty is moderately high • Decision space is structured • Desired explainability is high • Number of decision variables is moderately high • Decision time is moderately long • Adequate computing capability is given	• Deterministic or stochastic predictive model

Prescriptive Methods

The choice of prescriptive method depends first and foremost on the chosen predictive method and the desired AC. For low desired AC, or more specifically for the predictive decision variable set, no predictive method is chosen at all. When the predictive method does not allow for an optimisation method, one of the metaheuristics has to be used. In some cases, the metaheuristics may also enable faster decisions, usually in the form of hybrid methods. Alternatively, a corresponding meta model can be trained on the predictive model to enable using optimisation. Table A 10 provides an overview of the methods usage criteria and dependencies.

Table A 10: Selection Criteria for Prescriptive Methods

Category	Method	Selection Criteria	Dependencies
Optimisation	Linear Optimisation	• Number of decision variables is very high • Desired AC is very high • Decision time is very short	• Linear predictive model
	Mixed Integer Optimisation	• Number of decision variables is very high • Desired AC is very high • Decision time is short	• Mixed integer linear predictive model or multi-adaptive regression spline as meta-model
	Dynamic Optimisation	• Number of decision variables is very high • Desired AC is very high • Decision time is short • Decision variables can be structured in largely independent sets	• Deterministic or stochastic predictive model or corresponding meta-model
	Quadratic Optimisation	• System is captured well using quadratic functions • Number of decision variables is moderately high • Desired AC is high	• Quadratic predictive model or response surface
	Stochastic Optimisation	• System behaves mostly linearly • Uncertainty is high • Number of decision variables is moderately high • Desired AC is high	• Stochastic predictive model or corresponding meta-model
Metaheuristics	Population-based Approaches	• Prediction can be parallelised well • Decision speed is more important than decision quality	
	Trajectory-based Approaches	• Prediction times are long and cannot be easily parallelised • Decision speed is more important than decision quality	

Decision Selection Methods

To determine the decision selection methods the desired AC and the quantifiability is important. In addition, the perspective diversity in the decision process and the available decision time should be taken into consideration. Some of the methods rely on specific prescriptive models. Additionally, some of the methods rely on predictive or prescriptive models that can be computed relatively quickly[87]. The overview of methods and corresponding selection criteria and dependencies is shown in Table A 11.

Table A 11: Selection Criteria for Decision Selection Methods

Category	Method	Selection Criteria	Dependencies
Multi-Attribute Decision Making	Value Measurement	• Desired AC is moderately low • Decision time is short	
	Reference Level	• Absolute quality of solutions is difficult to determine • Quantifiability is moderate • Desired AC is moderately low • Decision time is moderately short	
	Outranking	• Absolute quality of solutions is difficult to determine • Quantifiability is low • Desired AC is low	
Multi-Objective Decision Making	a-Priori Weighing	• Quantifiability is high • System is captured well using quadratic functions • Number of decision variables is moderately high • Desired AC is high	• Optimisation model

[87] Usually, the computation has to be completed within minutes to enable interactive decision-making for example.

Category	Method	Selection Criteria	Dependencies
		• Decision time is short	
	a-Posteriori Weighing	• Quantifiability is high • System behaves mostly linearly • Uncertainty is high • Number of decision variables is moderately high • Desired AC is high • Decision time is moderately long	
	Interactive Approaches	• Quantifiability is high • Desired AC is high • Desired explainability is high • Decision time is moderately long	• Fast model
Sensitivity Analysis		• Uncertainty is high • Desired explainability is high • Decision time is moderately long	
Post-Optimality Analysis		• Quantifiability is high • Uncertainty is high • Desired explainability is high • Decision time is moderately long	• Optimisation model
Multi-Stakeholder Decision Making Methods		• Perspective diversity is high • Decision time is moderately long	

Scenario Generating Methods

For scenario generating methods first the need to consider uncertainty has to be established. When the system behaves largely deterministic or if decision times are very short a consideration of scenarios may not be suitable. If the uncertainty is considerable different methods are primarily chosen by the type of uncertainty. In any case, if a prescriptive model is present, it needs to either be stochastic or use a metaheuristic in some form. For both predictive and prescriptive models, the computing speed can be critical when considering a large number of scenarios. If the number of scenarios needs to be reduced suitable clustering techniques can be applied. Multiple scenario generating methods can also be combined, corresponding to the considered external influences. Table A 12 provides an overview of the methods and corresponding selection criteria and dependencies.

Table A 12: Selection Criteria for Scenario Generating Methods

Method	Selection Criteria	Dependencies
Scenario Tech-niques	• Uncertainty is high • Time-horizon is long • Developments are dominated by large events • Decision time is moderately long	• Stochastic model, metaheuristic, or purely predictive model
Forecast-ing	• Uncertainty is high • Time-horizon is moderately short • Developments follow some pattern	• Stochastic model, metaheuristic, or purely predictive model
Receptor Model	• Uncertainty is high • Events do not directly translate to model parameters	• Stochastic model, metaheuristic, or purely predictive model
Monte-Carlo Simulation	• Uncertainty is high • Quantifiability is high • Parameters follow some known or estimated distribution	• Stochastic model, metaheuristic, or purely predictive model • Fast model or clustering

Method	Selection Criteria	Dependencies
Design of Experiments	• Uncertainty is high • Quantifiability is high • External development can be fully parametrised • Desired explainability is high	• Stochastic predictive model or corresponding meta-model

Meta-Modelling Methods

The choice of meta-modelling methods is purely optional. These models are used as a replacement for predictive or prescriptive models and offer a specialised structure and faster computation times. At the same time, they require training outside of the decision time, corresponding to multiple orders of magnitude the computing time for the original model and they lose accuracy. With these characteristics, they can afford the use of specialised optimisation models and allow for faster computation of solutions. In this, three principal uses are possible: (i) replacing a predictive model for predictive decision making, (ii) replacing a prescriptive model for prescriptive decision making, and (iii) replacing a predictive model for prescriptive decision making. The most suitable choice between (ii) and (iii) depends on the specific predictive and prescriptive models used and the desired decision times.

In general, meta-models are particularly useful if the training can be used towards multiple decisions, corresponding to high decision frequency. To choose between the meta-modelling methods, the desired scalability has to be considered. Table A 13 portrays the methods in order of ascending scalability but also ascending training input demands.

Table A 13: Selection Criteria for Meta-Modelling Methods

Category	Method	Selection Criteria
Regression Methods	Gauss Process Regression	• Training possibility is very limited • Model complexity is low • Decision time is low • Decision frequency is high
Regression Methods	Response Surface Models	• Training possibility is limited • Model behaves relatively smoothly and mostly follows quadratic expression • Quadratic approximation required • Decision time is low • Decision frequency is high
Regression Methods	Multi-Adaptive Regression Splines	• Training possibility is moderate • Model behaves relatively smoothly • Piece wise linear approximation required • Decision time is low • Decision frequency is high
Feed Forward Neural Networks		• Training possibility is high • Model complexity is high • Decision time is low • Decision frequency is high

A2.9 Model Relationships

In the following each type of relationship is defined and an illustrative example is given.

Primary Relationships

Primary Relationships are defined by a single overlap or lack thereof between two decision variable sets.

Dependent
A model m_2 is called dependent from m_1 if:

$$m_1 \Rightarrow m_2 \coloneqq X_{m_1}^{(SUB,PSC)} \cap X_{m_2}^{(FIX)} \neq \emptyset$$ *Equation A 51*

For example, if m_1 optimises the active production sites in a GPN prescriptively and m_2 is used to determine the active production equipment per site, $m_1 \Rightarrow m_2$ would be true. As a result, m_2 always has to wait for the results of m_1 and cannot easily influence it.

Semi-Dependent
A model m_2 is called semi-dependent from m_1 if:

$$m_1 \longrightarrow m_2 \coloneqq X_{m_1}^{(SUB,PDC)} \cap X_{m_2}^{(FIX)} \neq \emptyset$$ *Equation A 52*

For example, if m_1 predicts the costs of manually chosen changes in site activity and m_2 is used to determine the active production equipment per site, $m_1 \longrightarrow m_2$ would be true. As a result, m_2 has to wait for the results of m_1 and but experience from m_2 could influence it.

Independent
A model m_2 is called independent from m_1 if:

$$m_1 \nRightarrow m_2 \coloneqq X_{m_1}^{(SUB)} \cap X_{m_2}^{(FIX)} = \emptyset$$ *Equation A 53*

For example, if m_1 optimises the transport route selection between sites and m_2 is used to determine the active production equipment per site, $m_1 \nRightarrow m_2$ would be true. As a result, m_2 can be used without paying regard to m_1.

Conflicting
A model m_2 is called conflicting with m_1 if:

$$m_1 \Leftrightarrow m_2 \coloneqq X_{m_1}^{(SUB,PSC)} \cap X_{m_2}^{(SUB,PSC)} \neq \emptyset$$ *Equation A 54*

For example, if m_1 optimises the active production sites in a GPN and the production equipment used at each site prescriptively and m_2 is used to determine the shift model and active production equipment per site prescriptively, $m_1 \Leftrightarrow m_2$ would be true. As a result, m_2 and m_1 determine decisions on production equipment activity. These results cannot easily be coordinated, as both are determined automatically.

Semi-Conflicting
A model m_2 is called semi-conflicting with m_1 if:

$$m_1 \looparrowleft m_2 \coloneqq X_{m_1}^{(SUB,PDC)} \cap X_{m_2}^{(SUB,PSC)} \neq \emptyset \qquad \textit{Equation A 55}$$

For example, if m_1 predicts the costs of manually chosen changes in active production sites in a GPN and the production equipment used at each site and m_2 is used to determine the shift model and active production equipment per site prescriptively, $m_1 \looparrowleft m_2$ would be true. As a result, m_2 and m_1 determine decisions on production equipment activity. These results can be coordinated if the outcomes of m_2 are used as alternative in m_1.

Complimenting
A model m_2 is called complimenting m_1 if:

$$m_1 \rightleftarrows m_2 \coloneqq X_{m_1}^{(SUB,PDC)} \cap X_{m_2}^{(SUB,PDC)} \neq \emptyset \qquad \textit{Equation A 56}$$

For example, if m_1 predicts the costs of manually chosen changes in active production sites in a GPN and the production equipment used at each site and m_2 is used to determine the shift model and active production equipment per site predictively, $m_1 \rightleftarrows m_2$ would be true. As a result, m_2 and m_1 determine decisions on production equipment activity. These results can be coordinated by testing the same alternatives in both models and m_1 and m_2 may offer complimenting assessments on a decision.

Non-Conflicting
A model m_2 is called non-conflicting with m_1 if:

$$m_1 \nLeftrightarrow m_2 \coloneqq X_{m_1}^{(SUB)} \cap X_{m_2}^{(SUB)} = \emptyset \qquad \textit{Equation A 57}$$

For example, if m_1 optimises the transport route selection between sites and m_2 is used to determine the active production equipment per site, $m_1 \nLeftrightarrow m_2$ would be true. As a result, decision making does not have to be coordinated between m_2 and m_1.

Refining
A model m_2 is called refining m_1 if:

$$m_1 \rightsquigarrow m_2 \coloneqq X_{m_1}^{(INC,PSC)} \cap X_{m_2}^{(SUB,PSC)} \neq \emptyset \qquad \textit{Equation A 58}$$

For example, if m_1 optimises the active production sites in a GPN prescriptively and to determine the results prescriptively sets corresponding active production equipment at each site without acting on the latter and m_2 is used to determine the shift model and active production equipment per site prescriptively, $m_1 \leadsto m_2$ would be true. As a result, decisions-made by m_1 can be used as a comparison or starting point for m_2 but no restriction is placed on m_2. If the results generated in m_2 deviate significantly from what m_1 suggested, the factors leading to that can be questioned and models improved.

Rendering
A model m_2 is called rendering m_1 if:

$$m_1 \curvearrowright m_2 \coloneqq X_{m_1}^{(INC,PSC)} \cap X_{m_2}^{(SUB,PDC)} \neq \emptyset \qquad \textit{Equation A 59}$$

For example, if m_1 optimises the active production sites in a GPN prescriptively and to determine the results prescriptively sets corresponding active production equipment at each site without acting on the latter and m_2 is used to determine the shift model and active production equipment per site predictively, $m_1 \curvearrowright m_2$ would be true. As a result, decisions-made by m_1 can be used as a comparison or starting point for m_2 but no restriction is placed on m_2. Decision makers utilising m_2 can freely decide to deviate from the previous results based on the assessment and their expertise.

Optimising
A model m_2 is called optimising m_1 if:

$$m_1 \twoheadrightarrow m_2 \coloneqq X_{m_1}^{(INC,PDC)} \cap X_{m_2}^{(SUB,PSC)} \neq \emptyset \qquad \textit{Equation A 60}$$

For example, if m_1 predicts the costs associated with alternatives of active production sites in a GPN and to determine the results corresponding active production equipment at each site is determined manually without acting on the latter and m_2 is used to pre-scriptively determine the shift model and active production equipment per site, $m_1 \twoheadrightarrow m_2$ would be true. As a result, decisions-made using m_1 can be used as a comparison or starting point for m_2 but m_2 likely determines an optimised and deviating solution. Decision makers using m_1 may use m_2 to determine suitable alternatives if it can be used with reasonable effort.

Reevaluating
A model m_2 is called reevaluating m_1 if:

$$m_1 \rightsquigarrow m_2 \coloneqq X_{m_1}^{(INC,PDC)} \cap X_{m_2}^{(SUB,PDC)} \neq \emptyset \qquad \textit{Equation A 61}$$

For example, if m_1 predicts the costs associated with alternatives of active production sites in a GPN and to determine the results corresponding active production equipment at each site is determined manually without acting on the latter and m_2 is used to determine the shift model and active production equipment per site manually, $m_1 \rightsquigarrow m_2$ would be true. As a result, decisions-made using m_1 can be used as a comparison or starting point for m_2. Decision makers using m_2 reevaluate the proposed decision in light of additional, more detailed information.

Secondary Relationships

Hierarchically Superior
A model m_1 is called hierarchically superior to m_2 if:

$$m_1 \Rrightarrow m_2 \coloneqq (m_1 \Rightarrow m_2) \wedge (m_1 \nLeftarrow m_2) \qquad \textit{Equation A 62}$$

For example, if m_1 optimises the active production sites in a GPN prescriptively and m_2 is used to determine the active production equipment per site, $m_1 \Rrightarrow m_2$ would be true. As a result, decisions made in m_2 are always in relation to a previously made decision in m_1.

Interlocked
A model m_1 is called interlocked with m_2 if:

$$m_1 \rightleftarrows m_2 \coloneqq (m_1 \Rightarrow m_2) \wedge (m_1 \Leftarrow m_2) \qquad \textit{Equation A 63}$$

For example, if m_1 optimises the active production sites in a GPN prescriptively using the transportation costs between the sites as an input and m_2 optimises the transportation routes based on the active sites and their capacities, $m_1 \rightleftarrows m_2$ would be true. As a result, decisions made in m_2 are always in relation to a previously made decision in m_1 and vice versa. Whenever one makes a decision, the other one is automatically outdated.

Semi-locked
A model m_1 is called semi-locked by m_2 if:

$$m_1 \rightharpoonup m_2 \coloneqq (m_1 \Rightarrow m_2) \wedge (m_1 \longleftarrow m_2) \qquad \textit{Equation A 64}$$

For example, if m_1 optimises the transportation routes based on the active sites and their capacities and m_2 determines the active production sites in a GPN predictively using the transportation costs between the sites as an input, $m_1 \rightharpoonup m_2$ would be true. As a result, decisions made in m_2 are always in relation to a previously made decision in m_1 and vice versa. However, m_2 can test multiple alternatives considered for m_1 and provide the corresponding transportation costs.

A2.10 Strategies to Adress Model Relationships

In the following, the strategies to address the different types of relationships are inferred and described. These strategies may help to create suitable models in a complex process landscape that consists of multiple interacting decision processes. The strategies are structured by the category of relationship they address. An overview of the strategies is provided in Table A 14.

Table A 14: Overview of Strategies to Adress Model Relationships

Category	Addressed Relationship	Strategy	Strategy Type
Dependence	dependent, semi-dependent	sequence	organisational
		connect	procedural
Locks	interlocked	automatically iterate	
	interlocked and semi-locked	manually iterate	
		combine	model combination
		subsume	
		predictively explore	space combination
		prescriptively explore	
Conflicts	conflicting	combine	model combination
		subsume	
		clarify responsibility	organisational
		reduce capability	model change
		dynamically select trade-off	space combination
		predictively explore	
		prescriptively explore	
	complimenting	coordinate	organisational
		integrate	model combination
Realisations	refining, rendering	subsume	
	optimising	integrate	model combination
	reevaluating	expand	
	all realisations	sequence decreasingly	organisational
	optimising, reevaluating	sequence increasingly	
	all realisations	trigger	procedural
		calibrate	

Each strategy can be assigned to a strategy type, according to the main mode of resolution. These strategy types are (i) organisational, (ii) procedural, (iii) model combination, (iv) model change, and (v) space combination. Organisational strategies focus on changing the basic structure of the decision-making process. Procedural strategies change the order and connections between decision-making processes. Model combination strategies seek to join to models used for decision making into one. Model change strategies alter one of the models to avoid conflicts with the other one. Space combination strategies seek to join the decision-making space between two models and thus align their decision-making.

Dependence

Sequence
Sequencing specifies the order in which decisions are made. It addresses dependent and semi-dependent models, as the dependent model is only ever executed after the first one. This strategy requires relatively little effort. Difficulties may occur if this sequence cannot be guaranteed in the organisation.

Connect
Connecting directly binds the execution of the dependent model to the execution of the independent one. This addresses dependent and semi-dependent relationships. The connection may either be specified organisationally as a workflow or by implementing it directly in the DSSs.

Locks

Automatically Iterate
Iteratively uses two locked DSSs to find a preferred solution, by automatically transferring the changes in results from one DSS to the parameters of the other. This is only possible for interlocked DSSs, as the ability to automatically deduce the preferred solution is required. Automatic iteration requires a direct connection between both DSSs. The iteration may never converge or converge to non-dominant solutions. To induce convergence an increasing punishment for alterations can be applied, that incentivizes the DSS to find stable solutions. The iteration usually has to be stopped by a break criterion based on the iteration count or the solution stability. If either model is partially predictive, multiple iteration runs based on different partial strategies may be applied.

Manually Iterate
Iteratively uses two locked DSSs to find a preferred solution, by manual transfer of the parameters. This can be applied in case of bot interlocked and semi-locked relationships. The number of feasible iterations is limited due to the necessary effort associated with manual interventions. Thus, this option is most suitable in situations where a fast convergence is likely.

Combine
Merges two models into a single model to avoid difficulties created through locks. This allows for the identification of optimal solution, provided both models are prescriptive, and the solution method is capable. When combining two models, several aspects have to be taken into consideration. The size and complexity of the resulting model should not exceed the limitations of the solution method. The formulation of the models should

be compatible both in terms of linearity as well as the definition of variables, parameters, scenarios, and time periods. This is particularly relevant if the resulting model is intended to be prescriptive. The organisational integration of both models needs to be aligned. In particular, both models should be operated by the same user, and the stakeholders should largely overlap.

Subsume
Integrates the lower AC model into the higher AC model, ensuring that the overall decision can be made with the desired AC level. This requires the solution method of the higher AC model to be capable of solving the other model, thus compatibility in terms of formulation, variables, parameters, scenarios, and time periods has to be given.

Predictively Explore
Makes the locked feasible decision space of two models explorable manually. For this, the feasible decision space of each model needs to be determined. In the shared space, possible combined solutions are determined manually and completed by each model. Then the results gathered with each model for each explored combination in the feasible decision space are identified and evaluated. This strategy is conceivable with both predictive and prescriptive models, though predictive models limit the number of explorations runs due to the effort associated with them. If the locked feasible decision space is small, this solution is attractive, as it avoids complex methods and can in principle find global optimal solutions. As with combination and subsumption, predictive exploration requires the overall process and users to be reconcilable with a joint execution. The models do however not have to be compatible to the same extent. Furthermore, the implementation effort compared to a combination is limited, as only exchange procedures have to be implemented.

Prescriptively Explore
Explores the locked feasible decision space between two models automatically by utilising meta-heuristics. The decision space is specified by the metaheuristic and both models provide the resulting value for each tested strategy. This procedure may be repeated for a set of instances of the joint predictive decision space of both models as chosen by the user. The strategy is more laborious to implement than predictive exploration but allows for a more efficient consideration of all alternatives.

Conflicts

Combine

Combines two models into one, so that the conflicted part of the joint decision space can be resolved in accordance with the combined objectives of both decision processes. When combining two models, several aspects have to be taken into consideration. The size and complexity of the resulting model should not exceed the limitations of the solution method. The formulation of the models should be compatible both in terms of linearity as well as the definition of variables, parameters, scenarios, and time periods. In some cases, it may be necessary to restructure both problems resulting in an abstracted combined model, on which two specialised models are dependent. Then the conflict between the two original model is resolved by the combined abstracted model and the dependent models determine the details of each decision. Furthermore, the decision processes themselves have to be adapted to support a joint decision.

Subsume

If the models have different AC levels, the lower AC model may be subsumed by the higher AC model, such that the desired overall AC level can be ensured. Depending on the compatibility of both models, this may require comprehensive adaptions of the subsumed model. Furthermore, the same limitations that apply for combinations have to be considered.

Clarify Responsibility

Specifies which decision process is primarily responsible for each part of the conflicted decision space. Subsequently, the non-responsible process is limited and uses the results of the responsible decision process as an input. This strategy can be relatively easy to implement but may require organisational changes. Furthermore, the clarification can subsequently lead to locks if both processes retain a part of the responsibility.

Reduce Capability

Reduces the AC of the models to arrive at a complimentary relationship, where the decision can be made jointly on the basis of the combined evaluation. This is typically relatively simple to implement but may make the decision process more laborious and requires coordinated experimentation between the DMCs of both decision processes.

Dynamically Select Trade-Off

Determines the loss in objective a secondary decision process makes by fixing the conflicted decision variables to the desire of the primary decision process. Then gradually releases the constraint on the secondary process to identify trade-offs between the decisions. The concept can be implemented by modelling the proximity to the solution of the primary decision process as a soft constraint that is gradually released to determine a series of compromises between the two models. For each compromise determined by a constrained deviation of the secondary model m_2 from the ideal result of the primary model m_1, the resulting outcome V_{m_1} in terms of m_1 has to be determined. Ideally the process is performed symmetrically for both decision processes. This process cannot guarantee to find the ideal compromise, as it only considers proximity to the selected strategy of the primary process and not the proximity to the objective value. This is illustrated in Figure A 1 where the dynamically select trade-off strategy is portrayed. Here p refers to the enforcement strength of the proximity constraint, with $p = 1$ indicating full enforcement as a hard constraint and $p = 0$ indicating no enforcement. The strategy is relatively simple to implement, as it does not require drastic changes to either model and thus allows models with very different solution methods to interact.

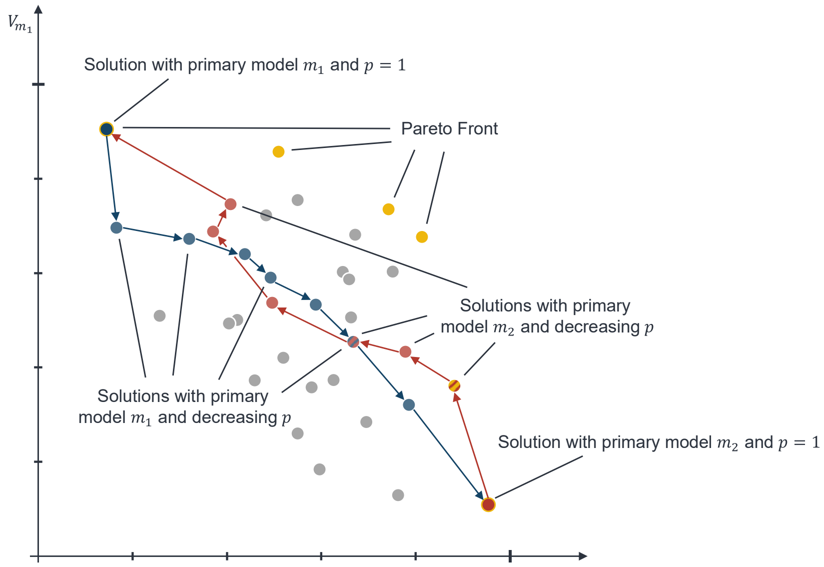

Figure A 1: Illustration of Dynamic Trade-Off Selection Strategy

Predictively Explore

Explores the conflicted decision space manually using methods from DoE. After establishing the joint feasible conflicted decision space, different combined configurations are tested by decision-maker intuition and experimental techniques. This allows for a systematic evaluation of the decisions and a joint evaluation. It is however limited in terms of the comprehensiveness the decision space can be explored. This is relatively simple to implement, as both models do not have to be changed.

Prescriptively Explore
Explores the conflicted decision space using meta heuristics that query the original models. Using a dynamic weighing of the objectives, a Pareto Front of the examined solutions can be established. This method requires the implementation of the meta-heuristics and its connection to the models. The meta heuristic should be chose based on the computing efficiency of the models, to take advantage of parallelisation. This method also cannot guarantee the optimal overall solution.

Coordinate
Structures the decision-making process such that the two complimenting decisions are made at the same time and the investigated alternatives in the complimented decision space are shared. This requires the DMCs of both decisions to communicate closely with each other.

Integrate
Integrates the complimenting models into one to jointly assess the complimenting decision space. This is only attractive if the compatibility between both models and the respective DMCs is high as it requires substantial implementation effort.

Realisations

Subsume
Integrates the refining or rendering model m_2 into the refined or rendered model m_1 without altering the AC level of m_1. The subsequent decision is thereby made directly by m_1. The strategy is only viable if the models are very compatible as it requires substantial implementation effort. Furthermore, computational limitations due to the increased complexity of m_1 have to be taken into account.

Integrate
Integrates the optimising model m_2 into the optimised one m_1 increasing its AC. Thereby decisions of m_1 may become more accurate and can directly be used for the optimising decision process. This requires high compatibility between both models and is associated with significant implementation effort.

Expand
Expands the reevaluated model m_1 with the reevaluating model m_2 to expand the decision-making authority. If both models are compatible the implementation effort is significant but limited, due to the predictive nature of the interaction.

Sequence Decreasingly
Structures decision-making processes such that the realising decisions are made directly after the realised ones. This is compatible with a sequence from more long-term, broad decisions that are refined into shorter-term decisions. The implementation effort required is low.

Sequence Increasingly
Structures decision making processes, such that the results of the optimising or reevaluating processes are used to infer the realised decision space for the optimised or reevaluated model. This allows overarching decisions to be made more quickly and a realistic foundation in the overall system. The implementation effort required is relatively low, though a degree of coordination is necessary.

Trigger
Automatically induces the execution of the realising model when new results of the realised model are available or vice versa. Increases the overall decision-making speed of the organisation. Requires moderate implementation effort.

Calibrate
Automatically calibrates the realised model using results from the realising models to improve the decision-making accuracy. Requires the prior or iterative execution of the realising model and has significant implementation effort.

A3 Base Model Architecture Resources

A3.1 Reference Data Model

The Reference Data Model is the result of the Masters theses A_Orhan (2022) and A_Weidmann (2021). The DM serves as a basis for the creation of company-specific data models. To create a DM suitable for the majority of PNC tasks, a systematic analysis of PNC tasks using representative literature is carried out and relevant modelling objects are recorded. These objects include the PNC Elements discussed earlier but also objects commonly found in related domains. Next, the elements are represented as classes and properties of the elements are identified based on the requirements of the planning tasks. This also results in the creation of subclasses where appropriate. Subsequently, relationships between classes are identified and described. Finally, the classes are structured in a DM, with subdivisions into coherent modules.

The resulting DM is portrayed in Figure A 2. It consists of seven modules, with strong inner and relatively weak outer connections. The modules are: (i) organisation module, (ii) location module, (iii) logistics module, (iv) resource module, (v) product module, (vi) order module, and (vii) process module. In the following the modules are briefly discussed.

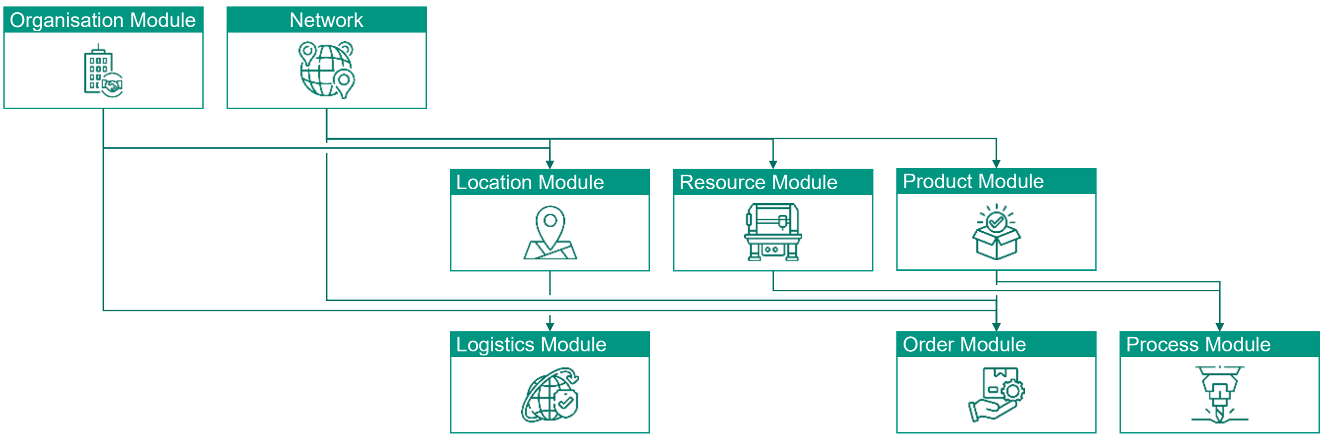

Figure A 2: Overview of the Reference Data Model

The organisation module depicted in Figure A 3 helps to describe interactions between an organisation and external stakeholders like customers and suppliers, but also interactions within the organisation, between business units. It also captures indirect functions of organisations and thereby *auxiliary capabilities*.

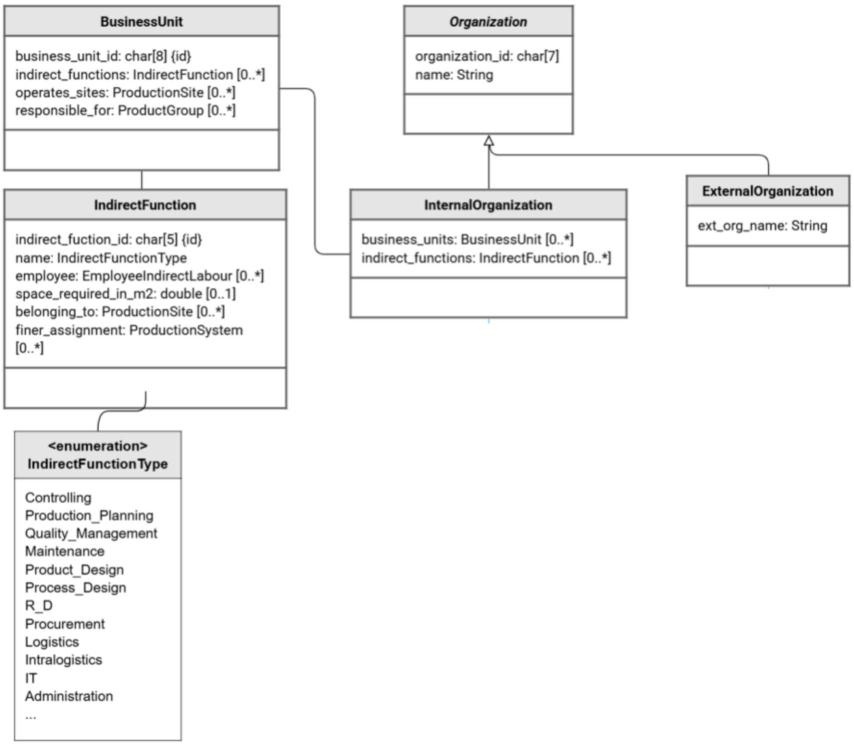

Figure A 3: UML Depiction of Organisation Module

Figure A 4 illustrates the location module. It describes the basic characteristics of a location. This basic type can be instantiated in different subtypes of locations commonly found in supply chains, like (i) production site, (ii) customer, (iii) supplier, (iv) warehouse, (v) distributor, and (vi) retailer. Each subtype also features a set of unique characteristics. As it is the main focus of this work, the production site location is captured in the most detail. The location module represents *production sites*, *auxiliary sites*, *logistic sites*, and *suppliers* from the PNC element library.

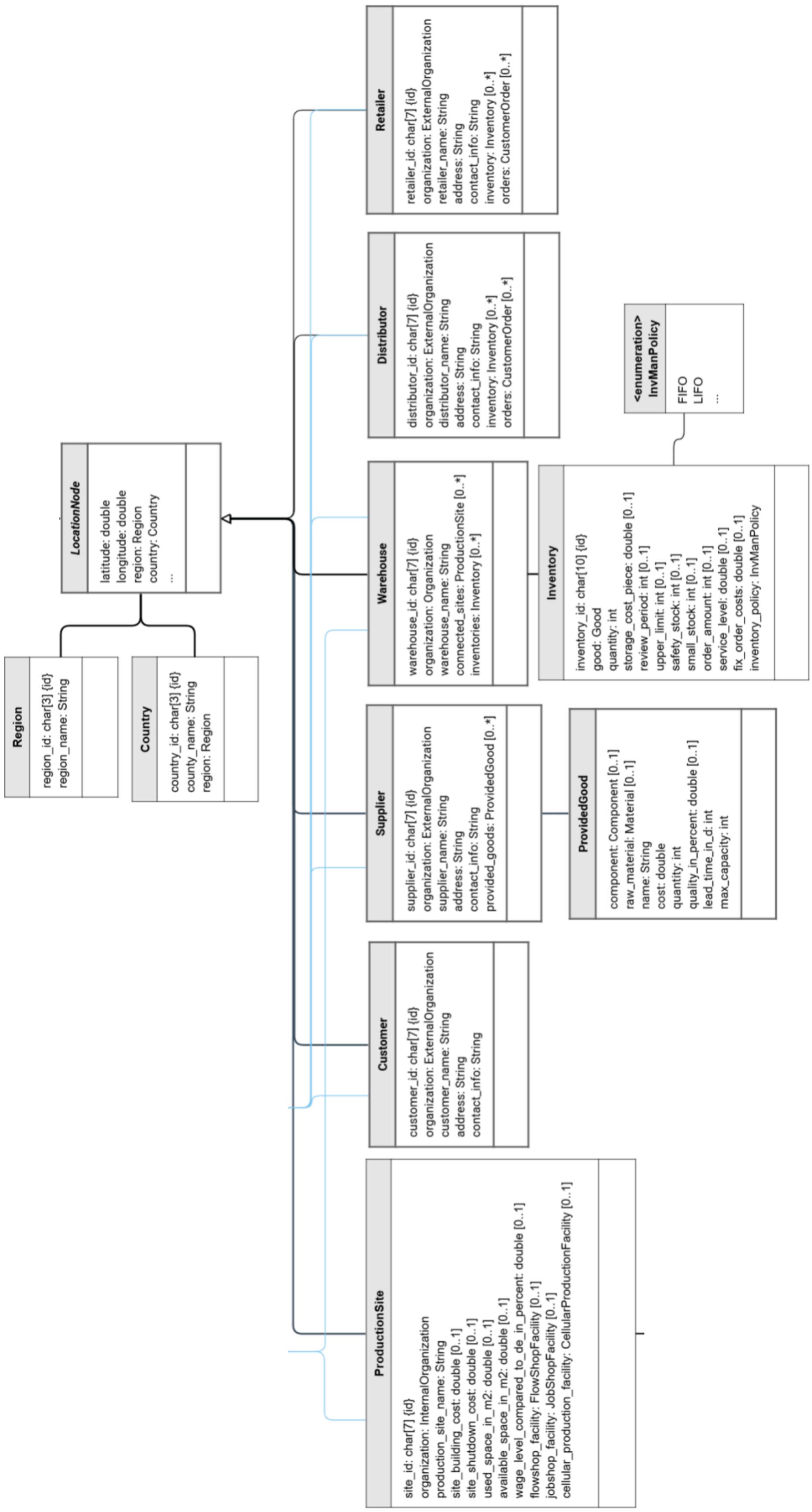

Figure A 4: UML Depiction of Location Module

A production site includes multiple resources, which are organised in production systems. The resources themselves are represented in the resource module, but the way they are utilised differs. Depending on the work system arrangement, these can for example take the form of lines, cells, or workshops. The production system is further specified using a set of characteristics as shown in Figure A 5.

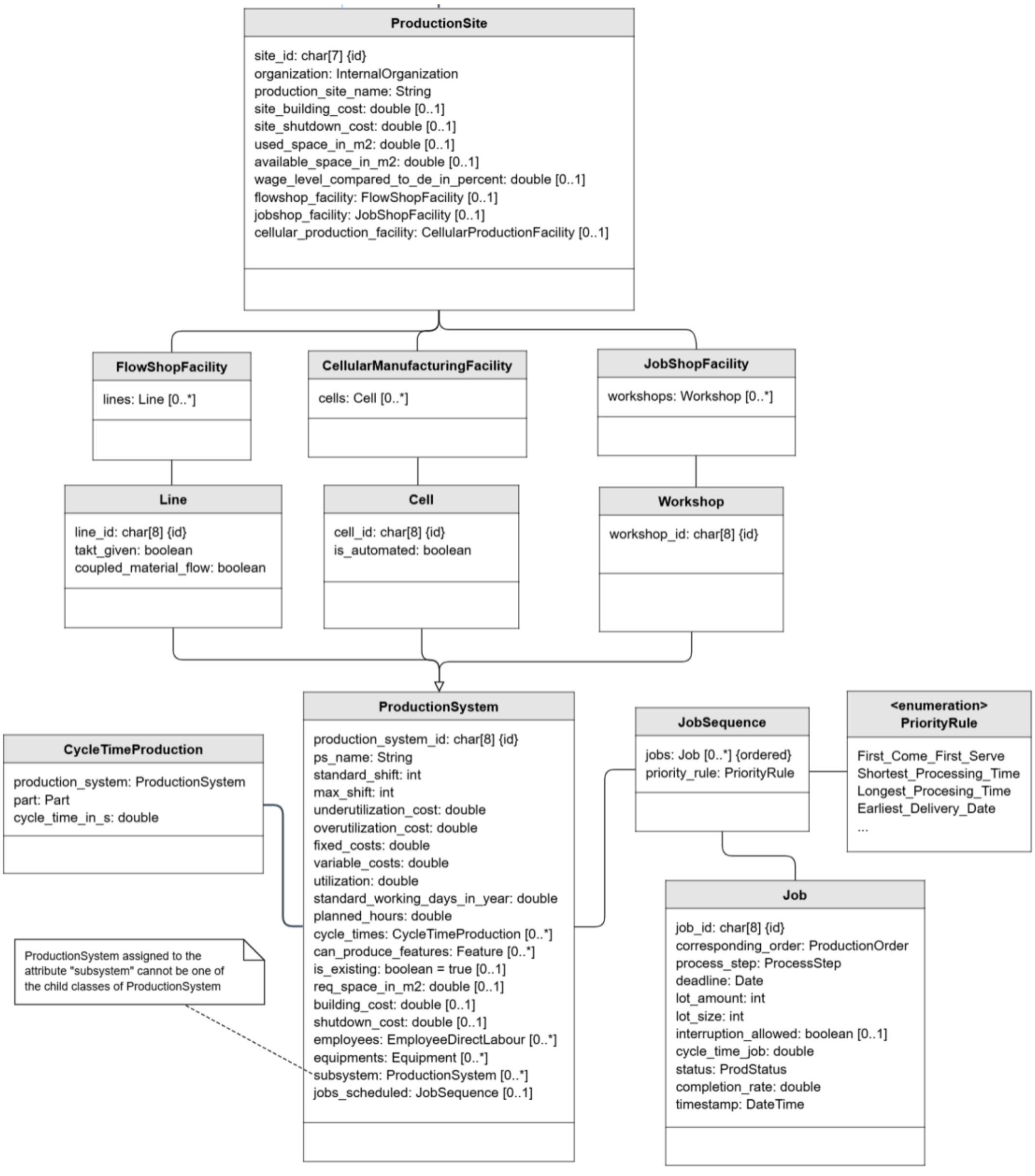

Figure A 5: UML Depiction of ProductionSite as Part of the Location Module

The logistics module describes transports of parts between locations. It contains several transport tasks, which are made up from several unimodal route legs. This allows the transport module to describe several different types of transport and represent *transport modes* from the PNC element library. Figure A 6 depicts the logistics module.

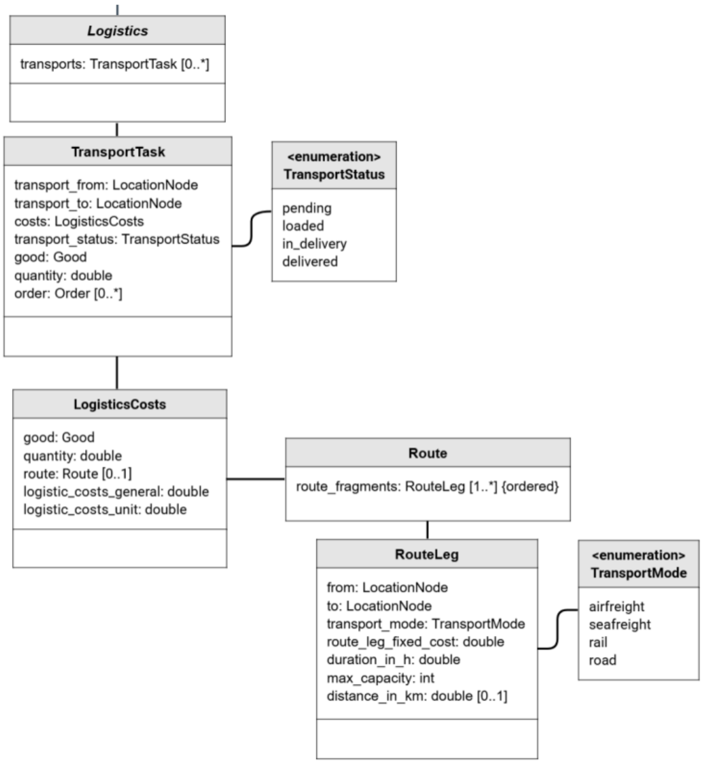

Figure A 6: UML Depiction of Logistics Module

The resource module displayed in Figure A 7 contains both equipment and labour which can be occupied by a production system. Equipment describes machines, plants, fixtures, and tools with a range of characteristics. In particular, different equipment types and status are distinguished. This represents the *production equipment*, *tools,* and *set-up* from the PNC element library. Labour is subdivided into directly and indirectly value creating employees representing *personnel* and *work time models*. The former are further described using capabilities necessary to match them to equipment.

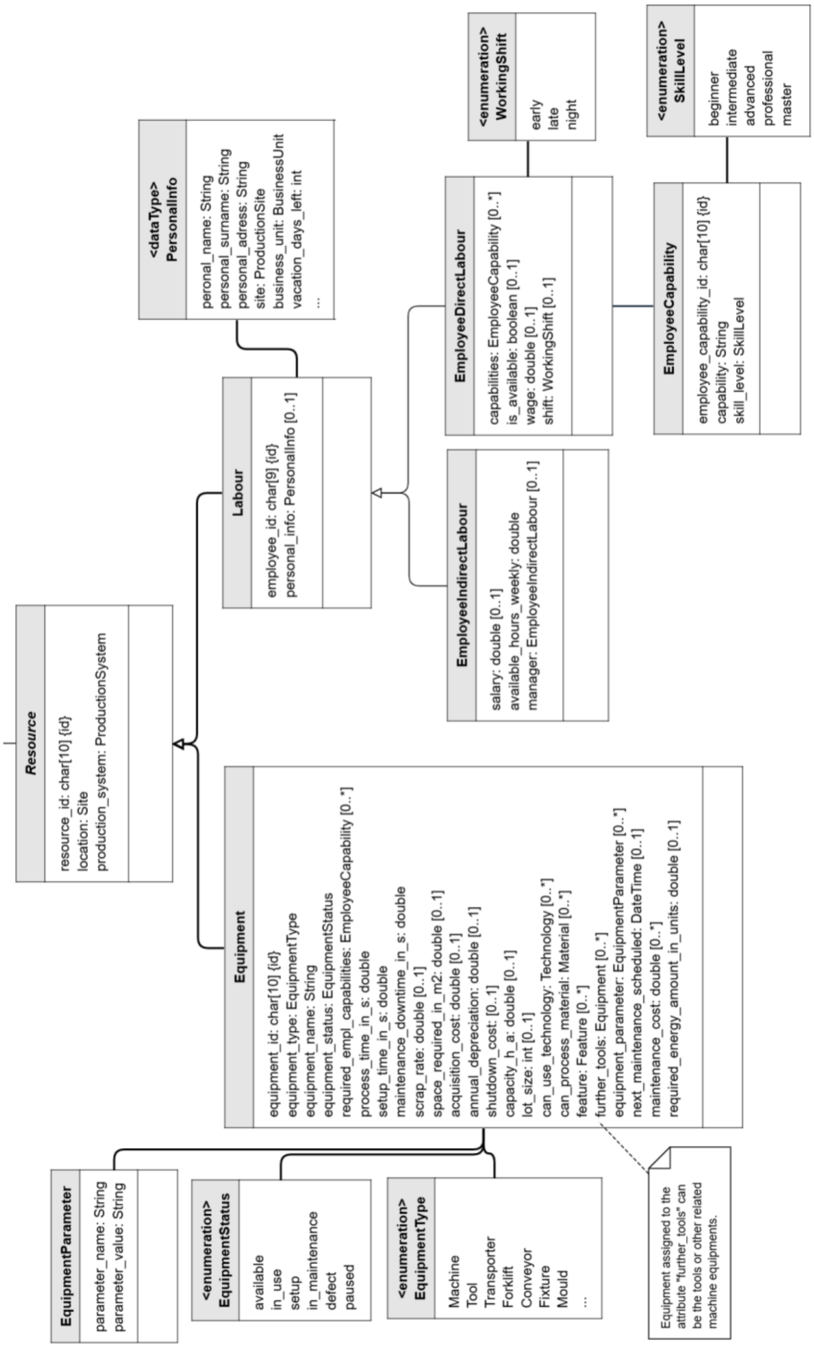

Figure A 7: UML Depiction of Resource Module

As Figure A 8 illustrates, the product module contains a set of products, which are organised in product groups, which in turn belong to a product portfolio. Each product is characterised by features, which are defined by a technology, which establishes the connection to a specific type of equipment and also represents *technologies* in the PNCE Element library. Products contain a bill of material, consisting of components and material. This allows the proposed structure to capture even complex product architectures.

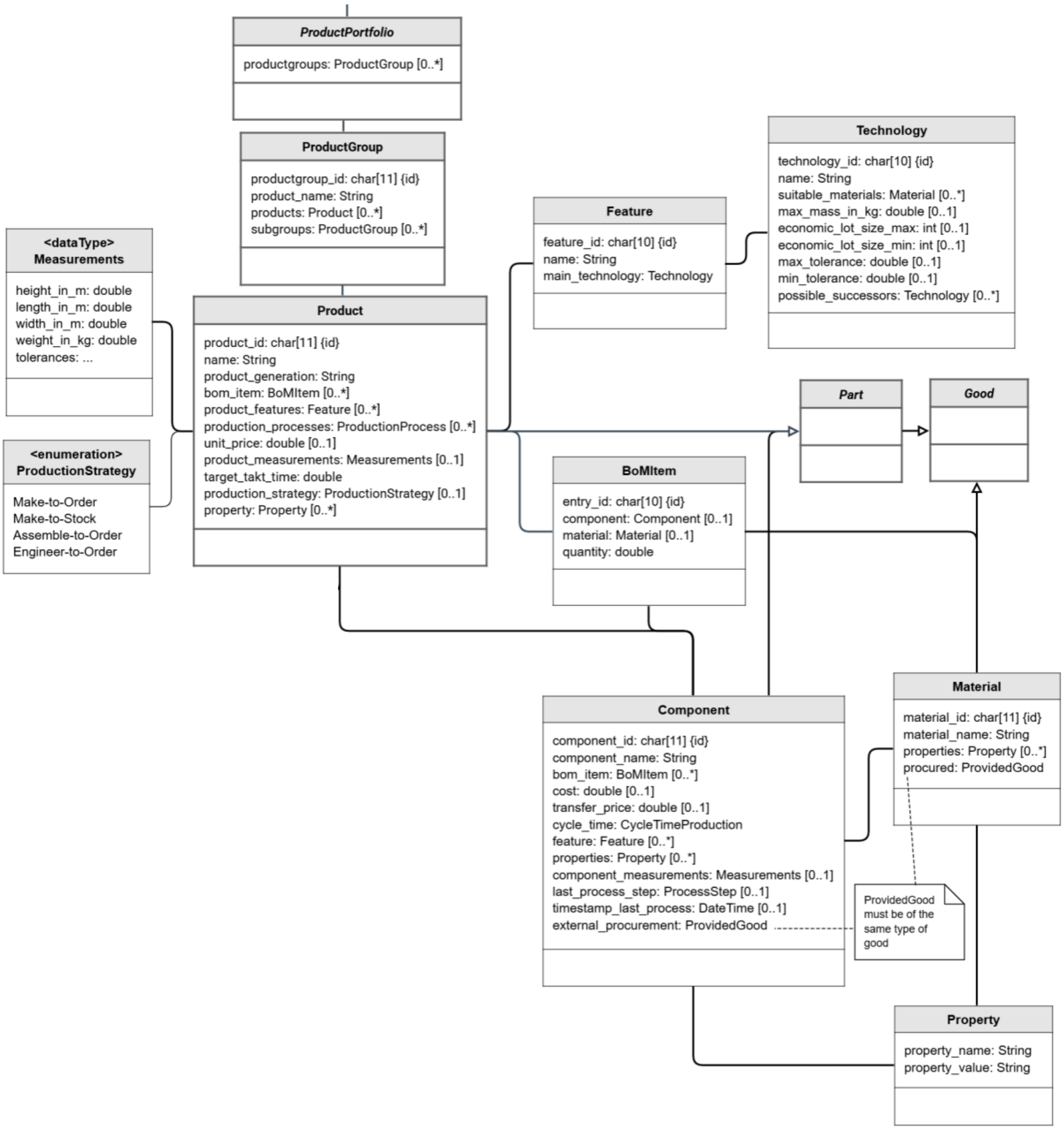

Figure A 8: UML Depiction of Product Module

The order module contains different types of orders that can occur in production networks. They can be differentiated into orders from suppliers, order for internal production and customer orders.

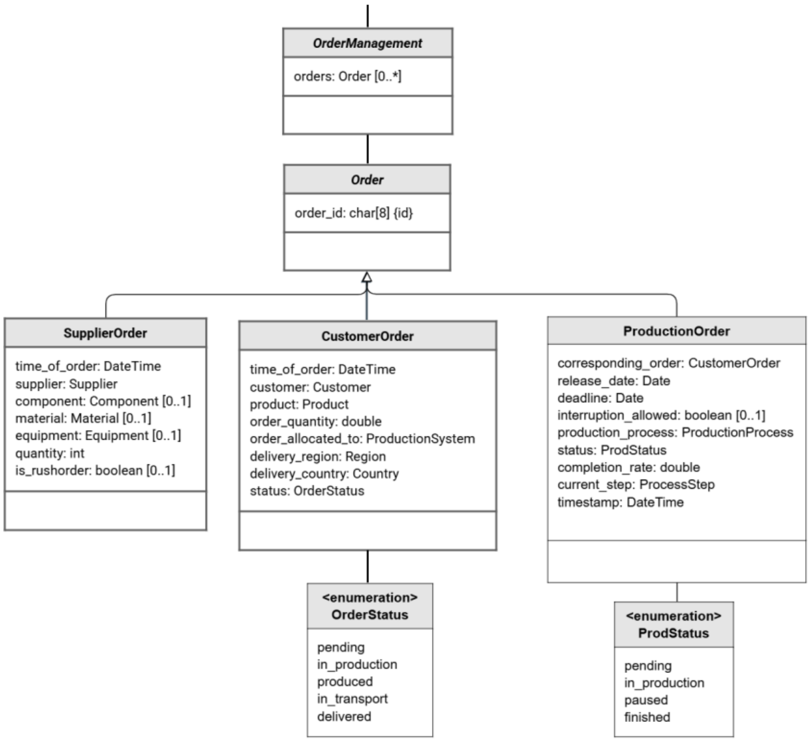

Figure A 9: UML Depiction of Order Module

The process module represents the production processes conducted by qualified employees on equipment using a set of inputs to create a set of outputs.

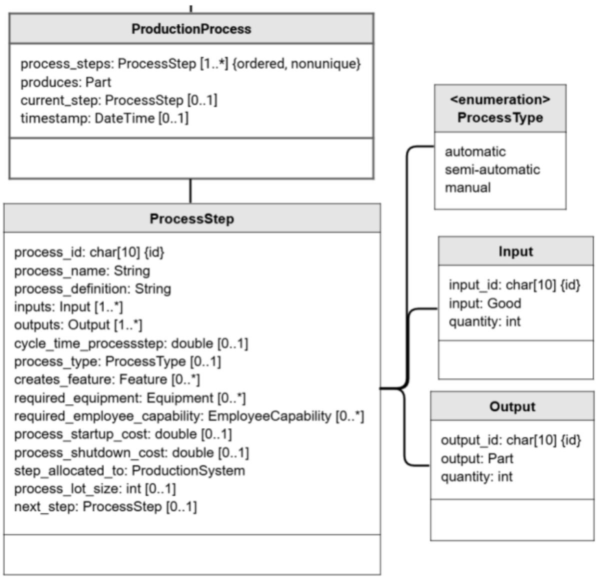

Figure A 10: UML Depiction of Process Module

The presented reference DM is a basis for individual DMs used in DBs.

A4 Data Acquisition Resources

A4.1 External Data Sources

In the following an analysis of the external data sources identified in this work is shown. In particular, the public availability, possible access forms, trustworthiness variants and selected use cases for the different sources are introduced. The result of this analysis is shown in Table A 15.

Table A 15: Assessment of External Data Sources for PNC Tasks

Source	Public Availability	Access Form	Trust-worthi-ness	Potential Use-Cases in PNC.
Economic trends (macro indicators & forecasts)	open (IMF, World Bank), commercial (EIU, McKinsey)	APIs, bulk files, dashboards, reports	++	Site selection, demand & capacity forecasts
Customer surveys / consumer demand	limited / proprietary (Nielsen, Ipsos)	Reports, dashboards, raw panels (paywall)	+	Market sizing, product-mix / allocation
Patent databases	open (WIPO, USPTO, EPO), proprietary analytics (Derwent, Questel)	Web portals, bulk XML, APIs, analytics tools	++	Technology planning, site clustering around R&D hubs
Trading prices for materials (commodities)	open (IMF, World Bank), proprietary real-time feeds (Bloomberg)	CSV, APIs, terminals, dashboards	++	Cost modelling, sourcing & hedge strategy
Economic figures (GDP, inflation, rates)	open (World Bank, OECD, central banks)	APIs, spreadsheets, data portals	++	Investment planning, scenario modelling
Worker availability (labour supply metrics)	open (ILO, national LFS)	Data browsers, CSV, APIs	++	Site selection, capacity & hiring plans
Energy costs (electricity, fuel)	open (EIA, Eurostat), proprietary (wholesale price services)	APIs, Excel, regulatory filings, terminals	++	Operating-cost modelling, location choice
Labour costs (wages)	open (ILO, OECD), proprietary (Mercer, WTW)	CSV, PDFs, survey portals	+	Cost modelling, labour-intensity decisions
Emission catalogues / LCA factors	open (IPCC EFDB, EPA), proprietary (ecoinvent, GaBi)	Online search, downloads, LCA software	++	Sustainability assessment, carbon-cost modelling
Logistic costs (freight rates)	open indices (BDI, FBX), proprietary quotes	Web charts, CSV, booking portals, APIs	+	Transport-cost modelling, network design
Logistic monitoring (port & in-transit visibility)	open stats (UNCTAD, port data) + proprietary control-towers (project44)	Dashboards, AIS feeds, APIs	+	Lead-time control, disruption response
Disruption monitoring (natural, geopolitical)	open (GDACS, USGS, ACLED)	Live maps, RSS/APIs, CSV	++	Risk mitigation, contingency planning
Local education levels / skills	open (UNESCO UIS, WB EdStats)	Web tables, CSV, reports	++	Talent pool assessment, R&D, or plant siting
Employee turnover indicators	open proxies (BLS JOLTS, OECD tenure), proprietary HR surveys	APIs, CSV, survey portals	+	Workforce stability, retention cost planning
Trade policy database (tariffs, NTMs)	open (WTO, WITS, ITC Trade Map)	Web tools, Excel, APIs	++	Tariff impact, sourcing & localization strategy
Legal security (rule of law)	open (World Bank WGI, WJP)	CSV, scorecards, PDFs	++	Investment risk screening, contract-enforcement planning
Political stability indices	open (WGI, Fragile States Index, Global Peace Index)	CSV, interactive maps, reports	+	Country-risk ranking, resilience planning

A4.2 Preprocessing Methods

Table A 16 shows available methods from knowledge discovery in databases that can be used to prepare data before importing it into DSSs. For each method, a brief description is provided. In the following the use of the considered categories is discussed.

Table A 16: Overview of Data Preprocessing Methods According to According to García et al. (2015) and Han et al. (2023)

Step	Category	Variant	Description
Cleaning	Imputation	Discard (Listwise deletion)	Remove records with missing fields
		Expectation Maximisation (EM)	Iterative maximum-likelihood fill-in of missing data
		Multiple imputation	Repeated stochastic imputation, then result averaging
		Bayesian Principal Component Analysis (PCA)	PCA-based missing value prediction with Bayesian tuning
		K-nearest neighbour (KNN)	Fill missing with values from similar records (neighbours)
		K-means clustering	Impute by cluster – use cluster prototypes for missing
		Support Vector Machine (SVM)	Predict missing using SVM treating “missing” as a class
		Local least squares	Regress missing attribute from local similar features
		Hot deck	Use actual value from a “similar” donor record
	Noise Reduction	Ensemble filter	Vote-based removal of noisy instances using multiple models
		Cross-validated committees	Noise filtering via cross-validated model committees
		Iterative partitioning filter	Iteratively purge noise via repeated re-training
Data Integration	Schema Matching	Rule-based	Match schemas via hand-crafted rules/logic
		Label-based	Match by comparing attribute names/labels
		Instance-based	Match by comparing actual data values
		Structure-based	Match via schema structure/context
		Embeddings	Match using learned vector representations
	Redundancy Elimination	Chi-squared correlation	Chi-square test to flag correlated categorical attributes
		Pearson correlation	Linear correlation to find redundant numeric fields
		Cosine-similarity	Similarity of vectors (angle between feature vectors)
		Edit distance	String edit distance (min. character edits to match)
		Jaro (Jaro-Winkler)	String similarity for short names (accounts for typos/transpositions)
		Token-based similarity	Similarity of sets of tokens (words)
		Bayesian decision rules	Probabilistic matching using Bayes (Fellegi–Sunter model)
		Support Vector Machines	ML classification to detect duplicates/redundant items
		Clustering	Group similar records, treat each group as one entity
Transformation	Normalisation	Min-max normalisation	Rescale numeric range to [minimax] → [0,1]
		Z-score normalisation	Standardize numeric data to mean 0, unit variance
	Advanced Transformation	Linear transformation	Apply linear function or projection to features
		Quadratic transformation	Include square (second-order) terms of features
		Polynomial approximation	Fit polynomial functions to data for smoothing
		Non-polynomial approximation	Use non-polynomial basis functions (splines, exponentials)
		Rank transformation	Replace values by their rank order
		Box-Cox transformation	Power transform to stabilize variance and normalize
		Nominal-to-binary	Convert categorical attribute to binary dummy variables
		Encodings	Convert categories via code or embedding (e.g. label, binary code)
		Embeddings	Dense vector representation of categorical/text data
	Dimensionality Reduction	Principal component analysis	Orthogonal linear components capturing maximal variance
		Factor analysis	Model many variables via a few latent factors
		Multidimensional scaling	Project items into lower-dimensional space preserving distances
		Clustering	Dimension reduction via grouping (cluster prototypes)
		Local linear embedding	Nonlinear manifold learning preserving local structure
	Discretisation	Information-based	Use information gain/entropy to cut continuous values
		Statistical	Use statistical measures (distribution) for binning
		Rough sets	Discretize preserving discernibility (rough set theory)
		Wrappers	Search for optimal discretization via model feedback
		Binning	Direct interval partitioning of numeric ranges

Imputation

Imputation is used to remove or replace missing values in data, while faithfully representing the underlying phenomena. The most suitable method depends on the particular data in question, its relation to other available data and its use. General approaches are to discard the entry and all directly related values, to determine the most likely value on the basis of the available population of the same data type, or to impute data while inferring information from connected data.

Noise Reduction

Noise reduction seeks to remove incorrect data that is the result of wrong inputs or influenced by some phenomena that the data should not capture. Several filtering methods exist, that often consist of multiple models to capture corresponding sources or types of noise.

Schema Matching

Schema matching transforms input data that follows a particular schema into another, desired output schema. Often the translations between schemas are not explicitly defined, so methods that can effectively limit the manual translation effort are used.

Redundancy Elimination

Redundancy elimination seeks and eliminates data doubles. Whereas absolute identity is trivial to discern, especially manually entered data may contain redundancy that is expressed in similarity of entries. Depending on the type of data corresponding methods are available.

Normalisation

Normalisation rescales numerical values for use in specific methods that require it. Generally, normalisation can be performed based on absolute values or using standard deviations.

Advanced Transformation

Advanced transformation is a recalculation of inputs to outputs that follow specific, previously defined functions. This may be done on one or multiple inputs at a time and use a variety of underlying functions. Most methods focus on numerical values, but methods to transform categorical values also exist.

Dimensionality Reduction

Dimensionality reduction seeks to limit the size of data used in subsequent processes through the elimination of data dimensions. Depending on the data and the pursued objectives, different methods may be applied.

Discretisation

Discretisation reduces the data size by increasing granularity and clustering data into consistent bins that can be used by subsequent processes. Suitable methods depend on the data used and the intended purpose.

A5 Organisational Integration Resources

Table A 17: Symbols Used in Appendix A5

Symbol	Description	Unit
$\emptyset$	Empty set	
α	Empirical reduction factor limiting the computable number of feasible combinations	
$\Gamma_i^{(CV)}$	Capital value of DSS or implementation item i	[€]
$\Gamma_i^{(DQ)}$	Decision-quality benefit of item i	
$\Gamma_i^{(DS)}$	Decision-speed benefit of item i	
$\Gamma_i^{(DT)}$	Decision-transparency benefit of item i	
$\Gamma_i^{(RS)}$	Reaction-speed benefit of item i	
$\Gamma_i^{(SK)}$	System-knowledge benefit of item i	
$\Gamma_i^{(TL)}$	Task-learning-speed benefit of item i	
$\Gamma_i^{(US)}$	User-satisfaction benefit of item i	
$\Gamma_i^{(UC)}$	User-capacity benefit of item i	
ι	Nominal interest rate used in capital-value discounting	
$\kappa^{(YC)}$	Usage / discount factor derived from interest rate and time horizon	
$\widehat{\Lambda}^{(IS)}$	Implementation roadmap (vector of ordered items)	
$\pi_{i,o}$	Parameter value of item i for objective o (triangular-distribution centre)	
$\pi'^{(ENH)}_{d,o}$	Parameter improvement contributed by enhancing dependency d for objective o	
$\tilde{\pi}_{d,o}$	Parameter distribution for enhancing dependency d for objective o	
$\tilde{\pi}_{i,o}$	Triangular distribution of parameter value of item i for objective o	
$\boldsymbol{\pi}_{b,i^*}$	Parameter value vector of item variant i^* relevant for benefit b	
$\boldsymbol{\pi}_b^{(ENH)}$	Enhancement parameter value vector relevant for benefit b	
$\boldsymbol{\acute{\pi}}_{b,d}^{(ENH)}$	Enhancement parameter value vector of dependency d relevant for benefit b	
$\boldsymbol{\pi}_b^{(FIX)}$	Fixed parameter value vector relevant for benefit b	
$\boldsymbol{\pi}_{b,i}^{(FIX)}$	Fixed parameter value vector of item i relevant for benefit b	
ϕ_i	Decision frequency of item i (number of decisions per period)	[1/m]

Symbol	Description	Unit
ρ	Distance-norm exponent used in risk–preference aggregation	
θ	Generic angle representing an organisation's risk preference	[°]
θ_c	Natural risk-preference angle of combination c	[°]
θ_{c_2,c_1}	Crossover preference angle between combinations c_2 and c_1	[°]
$\theta_c^{(RIG)}$	Right border preference angle of combination c	[°]
$\theta_u^{(RIG)}$	Right border preference angle of chain u	[°]
$\theta_c^{(LEF)}$	Left border preference angle of combination c	[°]
$\theta_u^{(LEF)}$	Left border preference angle of chain u	[°]
Θ_c	Preference-angle range for combination c	
$a_{c,i}$	Binary indicator ($1\ =$ item i is contained in combination c)	
b	Index of a benefit/objective type	
B	Set of all objectives considered by the organisation	
c	Index of an implementation combination	
c_0	Starting combination	
$c^{(NEW)}$	Newly found combination	
$c^{(PRE)}$	Predecessor combination	
$c^{(SUC)}$	Successor combination	
$C^{(FC)}$	Set of all feasible item combinations	
$C_c^{(PC)}$	Set of predecessor combinations of combination c	
$C_c^{(SC)}$	Set of subsequent combinations from combination c	
C'_{c_1,c_2}	Set of combinations between combinations c_1 and c_2	
d	Index of a categorical or enhancing dependency	
$D^{(CAT)}$	Set of categorical dependencies	
$D^{(ENH)}$	Set of enhancing dependencies	
$D_i^{(ENH)}$	Set of enhancing dependencies acting on item i	
$e_{d,i}$	Indicator that item i fulfils dependency d	
$e^{(DYN)}$	Exponent determining dynamic discounting	

Symbol	Description	Unit
$f_b^{(PER)}$	Performance-scoring function for benefit type b	
$g_r^{(IMP,RES)}$	Cost rate of resource r	[€]
$g_i^{(LC)}$	Labour costs per decision for item i	[€]
$g_i^{(UC)}$	Usage costs per decision for item i	[€]
$\tilde{g}_x^{(IMP,RES)}$	Cost rate distribution of resource x	[€]
$G_i^{(IMP,EXT)}$	External implementation costs of item i	[€]
$G_i^{(INV)}$	Investment costs of item i	[€]
$G_i^{(OP)}$	Yearly operating costs of item i	[€]
$G_i^{(YC)}$	Total yearly costs of item i	[€]
i	Implementation item	
$i_d^{(DEP)}$	Item dependent on dependency d	
i^*	Implementation item variant	
I_c	Set of items corresponding to combination c	
$I^{(II)}$	Set of all implementation items	
$I_d^{(DEP)}$	Set of items fulfilling dependency d	
$I_m^{(FR)}$	Set of frontier items in iteration m	
I_c^*	Set of item variants corresponding to combination c	
I_m^*	Set of item variants in iteration m	
$k^{(REQ)}$	Demand of resource r to implement item i	[m]
$\tilde{k}_{i,x}^{(REQ)}$	Triangular distribution of demand of resource x to implement item i	[m]
$\dot{k}_x^{(AV)}$	Availability rate of resource x	[m/m]
$\tilde{\dot{k}}_x^{(AV)}$	Triangular distribution of $\dot{k}_x^{(AV)}$	[m/m]
$k_{i,x}^{(REQ,MIN)}$	Minimum resource demand of item i for resource x	[m]
$l_{i,d}^{(ITM)}$	Fulfilment level of dependency d by item i	
$l_{c,d}^{(COM)}$	Fulfilment level of dependency d within combination c	
m	Iteration counter in the roadmap algorithm	
n	Monte-Carlo sample index	

Symbol	Description	Unit
$N_m^{(AI)}$	Maximum items per combination in iteration m	
$N^{(EFC)}$	Estimator for the number of feasible combinations	
$N^{(FC,MAX)}$	Hard cap on feasible combinations per iteration	
$N_m^{(FR)}$	Number of items in the frontier in iteration m	
$N^{(II)}$	Total number of implementation items considered	
$N_c^{(II)}$	Number of independent items in combination c	
$N_m^{(MI)}$	Minimum items per combination in iteration m	
o	Index of an objective	
O_i	Set of objectives relevant for item i	
$p_{i,q}$	Quality-fulfilment score of item i on criterion q	
$p_{q,d}^{(REQ)}$	Required quality level of criterion q for dependency d	
$p_{q,d}^{(SAT)}$	Satisfactory quality level of criterion q for dependency d	
P_0'	Set of initial preferred combinations	
P_{c_1,c_2}'	Set of preferred combinations between combinations c_1 and c_2	
P_{c_1,c_2}''	Limited set of preferred combinations between combinations c_1 and c_2	
q	Index of a quality criterion	
$Q^{(QLT)}$	Set of quality criteria	
$r_{i,d}$	Indicator that item i depends on d	
$r_c^{(OPT)}$	Distance of combination c to the positive ideal	
$r_c^{(PES)}$	Distance of combination c to the negative ideal	
S_c^+	Separation of combination c from the positive ideal (TOPSIS)	
S_c^-	Separation of combination c from the negative ideal (TOPSIS)	
$t_c^{(IMP)}$	Implementation duration of combination c	[m]
$t^{(IMP,REF)}$	Reference realisation time used for dynamic discounting	[m]
$\bar{t}_i^{(BDP)}$	Average base decision time (without item i)	[d]
$\bar{t}_i^{(DP)}$	Average decision time (with item i)	[d]
Δt	Generic time difference	[m]

Symbol	Description	Unit
$\overline{\Delta t}_i^{(DEC)}$	Average decision-time difference yielded by item i	[m]
$\overline{\Delta t}_i^{(DTD)}$	Average detection-time decrease yielded by item i	[m]
$\overline{\Delta t}_i^{(LTR)}$	Average learning-time reduction yielded by item i	[m]
T_c	Value of combination c	
$T_c^{(STAT)}$	Static TOPSIS utility score of combination c	
$\dot{T}_c^{(STAT)}$	Static utility-increase rate of combination c	
$T_c^{(DYN)}$	Dynamically discounted utility value of combination c	
$\dot{T}_c^{(DYN)}$	Dynamic utility-increase rate of combination c	
u	Chain of combinations	
$v_{b,c}$	Weighed performance of combination c on benefit b	
v_b^+	Positive-ideal performance for benefit b	
v_b^-	Negative-ideal performance for benefit b	
Δv	Generic improvement in an objective's performance	
$\overline{\Delta v}_{i,o}^{(OP)}$	Mean performance improvement per decision on objective o	
w_b	Weight of objective type b	
$w_{q,d}$	Quality criteria weight for criterion q and dependency d	
$w_{i,o}^{(OW)}$	Weight of objective o for decisions relating to item i	
$w_i^{(DT)}$	Desirability of decision transparency for decision corresponding with i	
$w_i^{(DC)}$	Criticality of decision corresponding with i for reaction speed	
$w_i^{(SKI)}$	Importance of system knowledge for item i	
$w_i^{(LR)}$	Learning relevance for item i	
$w_i^{(SR)}$	Relevance of user-satisfaction improvements	
$w_i^{(SUC)}$	Significance of user-capacity increases	
$w_{q,d}$	Weight of quality criterion q in dependency d	
$w^{(OPT)}$	Weight assigned to the optimistic assessment in risk aggregation	
$w^{(PES)}$	Weight assigned to the pessimistic assessment in risk aggregation	
x	Index of a resource	

Symbol	Description	Unit
X	Set of all resources considered	
y	Year index in capital-value calculations	
$y^{(TH)}$	Time-horizon length (years) used for discounting	
$\mathbb{E}[x]$	Expected value of variable x	
$\varsigma[x]$	Standard deviation of variable x	
$\bar{\varsigma}[x]$	Average standard deviation of variable x	

A5.1 Benefits

In the following the different types of benefits achievable through DSS in PNC are discussed. Based on existing literature, three distinct decision-related benefits are distinguishable. Those are (i) the efficiency of the decision process, (ii) the decision quality, and (iii) the decision speed. Additionally multiple organisation-related benefits exist. Those are the transparency of decisions within the organisation, the ability to react to changes, the system knowledge of employees, the speed with which decision makers and other DSS users can acquire the knowledge for the decision process, the satisfaction of DSS users and the capacity of users that may be devoted to other issues.

Table A 18: Overview of DSS Benefits

Benefits	Description
Capital Value	Total economic value of the DSS, with regard to invested and saved resources.
Decision Quality	Expected improvements in decision quality in terms of the organisation's objectives multiplied by decision frequency.
Decision Speed	Decreases in time to make a decision.
Decision Transparency	Degree to which decisions are more traceable.
Reaction Speed	Decreases in speed of addressing unforeseen events.
User System Knowledge	Knowledge users an affiliated persons have regarding the system.
Task Learning Speed	Time users need to be able to perform the PNC tasks
User Satisfaction	Contentedness of users with their task.
User Capacity	Available capacity of users for other problems

In the following, each of the benefits is described and defined.

Capital Value

The efficiency of the decision process can be expressed in terms of the capital value of the DSS outside of the decision outcomes. This includes all investments necessary to design and implement the DSS and the costs of operating it. In cases where the DSS is used to replace a previously unsupported process, it also includes the difference in labour costs associated with the decisions. When DSS are used for new decision processes, which would previously not have been considered, this difference equals the labour costs associated with the decision. In summary, the capital value $\Gamma_m^{(CV)}$ of the DSS or other implementation items i may be expressed as follows:

$$\Gamma_i^{(CV)} = \overbrace{G_i^{(IMP,EXT)} + \sum_{r \in R^{(IMP)}} \left(k_{r,i}^{REQ} g_r^{(IMP,RES)}\right)}^{G_i^{(INV)}} + \overbrace{\sum_{y=1}^{y^{(TH)}} \left(\frac{1}{(1+\iota)^y}\right)}^{\kappa^{(YC)}} \underbrace{\left(G_i^{(OP)} + \phi_i\left(\overline{\Delta t}_i^{(DEC)} g_i^{(LC)} + g_i^{(UC)}\right)\right)}_{G_i^{(YC)}} \quad \textit{Equation A 65}$$

, where $G_i^{(IMP,EXT)}$ are the initial external costs to implement the DSS, $g_r^{(IMP,RES)}$ the costs rate of a resource r, $k_{r,i}^{REQ}$ is the resource specific demand to implement i, $R^{(IMP)}$ the set of relevant resources, and $G_i^{(INV)}$ the overall investment costs for i. The yearly costs $G_i^{(YC)}$, determined by the yearly operating costs $G_i^{(OP)}$, the decision frequency ϕ_i, the average decision time difference $\overline{\Delta t}_i^{(DEC)}$, the user labour costs $g_i^{(LC)}$, and the usage costs $g_i^{(UC)}$ are multiplied by the usage factor $\kappa^{(YC)}$, shaped by the interest rate ι and the time horizon $y^{(TH)}$. y denotes the year.

Decision Quality

The quality of the decision-making process results is typically best assessed using the organisations objectives, usually as applied in the decision process[88]. Thus, the benefit a DSS provides in terms of decision quality should be assessed in terms of its cumulative effect on the organisation's decisions. The decision quality improvement $\Gamma_i^{(DQ)}$ a DSS or another implementation item i provides can be estimated as follows:

$$\Gamma_i^{(DQ)} = \phi_i \kappa^{(YC)} \sum_{o \in O_i} \left(w_{i,o}^{(OW)} \overline{\Delta v}_{i,o}^{(OP)}\right) \quad \textit{Equation A 66}$$

where $o \in O_i$ are the objectives the decision quality is judged on, $w_{i,o}^{(OW)}$ describes the weight of the objective for the relevant decisions with $\sum_{o \in O_i}\left(w_{i,o}^{(OW)}\right) = 1$, and $\overline{\Delta v}_{i,o}^{(OP)}$ denotes the average performance improvement per decision on objective o[89].

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[88] In some cases, the ex-post assessment may concern more overarching objectives but generally, decisions should be made for the objectives they can affect and judged on those objectives.

[89] Here a relatively simple weight sum is used to estimate decision quality improvements, of course more complex MADM techniques could be employed.

Decision Speed

The decision speed $\Gamma_i^{(DS)}$ describes how much the DSS or other implementation item i is able to reduce the time necessary to make a decision. Thus $\Gamma_i^{(DS)}$ can be assessed as follows:

$$\Gamma_i^{(DS)} = \overbrace{\bar{t}_i^{(BDP)} - \bar{t}_i^{(DP)}}^{\overline{\Delta t}_i^{(DEC)}} \qquad \textit{Equation A 67}$$

where $\bar{t}_i^{(BDP)}$ denotes the average base decision time without i and $\bar{t}_i^{(DP)}$ the average decision time with i.

Decision Transparency

The decision transparency $\Gamma_i^{(DT)}$ measures the increase in desired decisions transparency of the organisation. As the desire for and importance of decision transparency differs by decision $\Gamma_i^{(DT)}$ is calculated as follows:

$$\Gamma_i^{(DT)} = w_i^{(DT)} \overline{\Delta v}_i^{(DT)} \qquad \textit{Equation A 68}$$

where $w_i^{(DT)}$ describes the desirability of transparency increase for the decision and $\overline{\Delta v}_i^{(DT)}$ the average transparency increase using i.

Reaction Speed

The reaction speed $\Gamma_i^{(RS)}$ measures the potential of the DSS to reduce the time necessary to react to a change. This is not limited to the decision time itself, instead it measures whether the item i allows organisations to perceive change requirements earlier. It is measured as follows:

$$\Gamma_i^{(RS)} = w_i^{(DC)} \overline{\Delta}\mathrm{t}_i^{(DTD)} \qquad \textit{Equation A 69}$$

where $w_i^{(DC)}$ denotes the criticality of the decision for reaction speed and $\overline{\Delta}\mathrm{t}_i^{(DTD)}$ the average detection time decrease using i.

User System Knowledge

The user system knowledge $\Gamma_i^{(SK)}$ describes the DSS or items contribution to the system expertise of a user. This contribution can be both positive or negative, if using the system decreases users' interactions with it and thus their understanding[90].

$$\Gamma_i^{(SK)} = w_i^{(SKI)} \overline{\Delta v}_i^{(SKC)} \qquad \textit{Equation A 70}$$

where $w_i^{(SKI)}$ denotes the importance of system knowledge with respect to the item i and $\overline{\Delta v}_i^{(SKI)}$ the average system knowledge change using i.

Task Learning Speed

The task learning speed $\Gamma_i^{(TL)}$ describes how much the item i decreases the time users need to understand and learn the decision-making task. Often DSS simplify decision-making processes by structuring them. However, for example, for users with lower model expertise, complex DSS may even increase the learning time. $\Gamma_i^{(TL)}$ is calculated as follows:

$$\Gamma_i^{(TL)} = w_i^{(LR)} \overline{\Delta}\mathrm{t}_i^{(LTR)} \qquad \textit{Equation A 71}$$

where $w_i^{(LR)}$ denotes the learning relevance for the process in terms of its prevalence and typical user expertise and $\overline{\Delta}\mathrm{t}_i^{(LTR)}$ the average learning time reduction using i.

User Satisfaction

The user satisfaction $\Gamma_i^{(US)}$ describes how content users of the DSS or other item i are with the decision-making process. This can be important to encourage adherence to process standards and users' inclination to recommend the DSS to others or help them. $\Gamma_i^{(US)}$ is measured as follows:

$$\Gamma_i^{(US)} = w_i^{(SR)} \overline{\Delta v}_i^{(SI)} \qquad \textit{Equation A 72}$$

where $w_i^{(SR)}$ denotes the relevance of satisfaction improvements with respect to the item i and $\overline{\Delta v}_i^{(SI)}$ the average change in satisfaction using i.

[90] In effect, users may consider the DSS a black box, which they do not understand.

User Capacity

User capacity $\Gamma_i^{(UC)}$ measures the importance of additional time afforded to users by utilising the system. In some cases, the time saving impact of a DSS may go beyond the saved wages of users, allowing them to concentrate on other important decisions and activities.

$$\Gamma_i^{(UC)} = \phi_i \kappa^{(YC)} w_i^{(SUC)} \overline{\Delta t}_i^{(DEC)} \quad \text{Equation A 73}$$

where $w_i^{(SUC)}$ denotes the significance of user capacity increases with respect to the item i.

A5.2 Model Application Types

In the following the procedure applied to determine application types for DSS and the result of this procedure are discussed.

Developing Model Application Types

To develop the taxonomy of model application types an iterative process defined by Nickerson et al. (2013) with additional inspiration from Kundisch et al. (2022) is applied. The process involves multiple steps, which are briefly described in Table A 19. Several intermediary iterations of the taxonomy are part of the thesis A_Krippner (2022), supervised by the author.

Table A 19: Development of Application Type Taxonomy Based on Nickerson et al. (2013)

Step		Description
1	Determination of Meta Characteristic	The application types should differ in terms of their interaction with users, and the objectives users pursue with them. They should not differ with regard to specific PNC tasks or DSS building methods outside of causal preferences for methods based on the application type.
2	Determination of Ending Condition	• The application types are clearly delineated from each other. • The taxonomy should cover application types with reasonable comprehensiveness. • Effects of individual application types on DSS design and expected benefits are clear
3-6	Building Approach	Multiple empirical-to-conceptual and conceptual-to-empirical passes.
7	Ending Conditions Check	The taxonomy contains mutually exclusive and collectively exhaustive categories. The resulting classifications are meaningful vis-à-vis DSS design. Objective ending conditions are met.

Application Types

In this section, the hierarchy of application types (AT) for DSS in PNC is detailed and each resulting application type is introduced.

Distinction by Objective

The primary distinction for application types lies in the objective pursued in their application. This work starts from a general notion that model-based DSS are most commonly used in *planning* problems where a specific action has to be selected. In that those DSS primarily address the design and choice phases of H. A. Simon's decision model. Thus, the decision quality provided by DSS in planning cases is particularly relevant. However, two other problems exist, in which DSS can support: (i) When do decisions need to be made? (ii) How does the system of consideration function? The first question reflects the need to *monitor* the system and its changes. Especially in complex systems like GPN, identifying relevant changes to act upon is nontrivial. Here DSS act as an instrument that evaluates consequences of changes which are easier to interpret and act upon. For those, the afforded reaction speed is particularly important. The second question addresses the need for general knowledge and intuition of complex systems behaviour. The DSS *teaches* decision-makers to grasp relationships and contingencies and prepares them for future decision-making situations. For such systems, the speed with which users are able to learn the task is particularly important.

Distinction by Occasion

Planning problems can arise in two general ways. The planning can be a *reaction* to a perceived change in circumstances that needs to be addressed, or the planning itself has been preplanned, *scheduled* to occur at a specific time. Reactive planning is typically time-sensitive, as the achievable performance may depend on the speed of decision making. It allows for less routine and puts an emphasis on explaining the results to a diverse set of stakeholders. In those ATs, benefits in terms of decision time are highlighted. Scheduled planning, by contrast, allows problems to be neatly sub structured ahead of time. It is also more suitable for shorter time horizons where decisions occur more frequently. In scheduled planning the capital value of DSS is particularly relevant.

Distinction by Trigger

The cause of reactive planning can either by *observations* made by responsible decision-makers in *individual reaction planning* (AT01) or *reaction rules*, set up ahead of time in *rule-based reaction planning* (AT02). When decisions are made upon observations, the planning situation typically is very unclear, so more effort has to be devoted to the intelligence phase. Overall, the effects coincide with lower ACs, as the DSS have to be more adaptive. When rules are predetermined that trigger the decision-making process, the process can be better prepared and thus more structured. These rules can be changes in the system itself or the environment. For example, the introduction of a new product could always trigger a new capacity and allocation planning occasion.

Distinction by Realisation

When planning is already prescheduled the way, those plans are implemented differs. In some cases, the decision may be implemented *automatically*, i.e., *scheduled planning with automatic realisation* (AT03). This is more typical in time-sensitive decisions, with high decision frequencies and cases where the decision can be implemented automatically. It coincides with high AC, as manual intervention would slow down the implementation and as the problems are suitable for high ACs in the first place. The most common application of DSS is another, however, where the decision is *determined* after planning, but additional manual intervention is necessary to implement it. This *scheduled planning with deterministic realisation* (AT04) is particularly suitable to typical DSS as it allows for scalability in the sense that similar decisions are made regularly but also requires individual user decisions. In some cases, planned decisions may be made in apprehension of a change or event, in order to improve reaction time. The realisation of those decisions is then *contingent* on external developments. In this *scheduled planning with contingent realisation* (AT05), decision makers want to put particular emphasis on scenario planning and the consideration of uncertainties[91]. Such contingency plans are particularly important when reaction speed is crucial. As many different scenarios can usually occur, this AT also coincides with increased decision frequency.

Distinction by Considered State for Monitoring

Monitoring applications are usually associated with tracking the *present* state of a system, but DSS with at least predictive capabilities also allow monitoring possible *future* states. *Trend monitoring* (AT06) is concerned with the former. Here the DSS is used to detect developments in the GPN that are not directly discernible from raw data. For example, the DSS may identify potentials to invest that have become more attractive based on changed market conditions. These indicators serve as triggers for subsequent planning processes. For such applications prescriptive capabilities are usually required, as the predictive abilities do not allow for corresponding decision triggers. *Risk monitoring* (AT07) applications systematically investigate future scenarios based on current developments in influencing factors. For those, the consideration of uncertainty is particularly important.

[91] While this AT is categorised as scheduled planning, there may be cases where the decision characteristics more closely resemble a reactive planning. For example, if specific events are observed to be likely, planning for that scenario may commence. In this work however, they are considered scheduled, as they do not react to something that has happened already, thus decision time does not necessarily affect reaction speed.

Distinction by Applicability
Teaching applications can either focus on knowledge regarding *specific setting* that users are interested in in or regarding the *general system*. For the specific settings, the availability of relevant data is more important. Another important characteristic is transparency regarding relations between different aspects that need to be investigated by the users. The second case is covered by *educational* (AT10) applications, which primarily serve to train users and improve their system expertise. Thus, they are particularly apt if the system expertise is low. As these applications focus more on general understanding, data availability is not as big of a concern. However, to enable adequate learning, investments in the interfaces and user guidelines have to be made, that may increase development efforts.

Distinction by Considered State for Teaching
Specific teaching applications can either address settings that occurred in the *past* to better understand what happened or explore *future settings*. *Diagnostic* (AT08) applications focus on enabling users to understand how and why decisions were made and what their consequences were. As such, decision transparency is a primary benefit of these applications. *Exploratory* (AT09) applications allow users to investigate a range of different future scenarios. Based on the results, further decision-making may take place. The consideration of uncertainty and availability of data is particularly important for those applications. They allow experienced users to advance their system knowledge and better grasp the importance of developments.

A5.3 Priority Assessment

The priority assessment establishes the implementation sequence for a range of possible implementation items that were previously identified following the development levels and directions of the PNC DT. It uses assessments of the potential benefits achieved through application-level items, improvements to application-level items realised through improved base model and data acquisition level items, required efforts to implement items and available implementation capacities. Each of these aspects may be estimated as a distribution or a specific value. The objective of the assessment is to realise the highest utility as quickly as possible while considering the risk preferences of the organisation. To address synergies and dependencies between different implementation items, the assessment is performed on item combinations. The items to be implemented are then sequenced in decreasing order of utility increase. The result of the process is a set of implementation roadmaps $\widehat{\Lambda}^{(IS)}$ which contain the implementation items in a sequence. The set of roadmaps covers a range of risk preferences, so that decision makers can chose the steps accordingly. Figure A 11 portrays the algorithm used to determine the roadmaps. In broad terms, it samples input values for items, enhancing dependencies and resources and iteratively develops roadmaps. The iterations are necessary to limit the computational complexity. The necessary steps are discussed in the following sections.

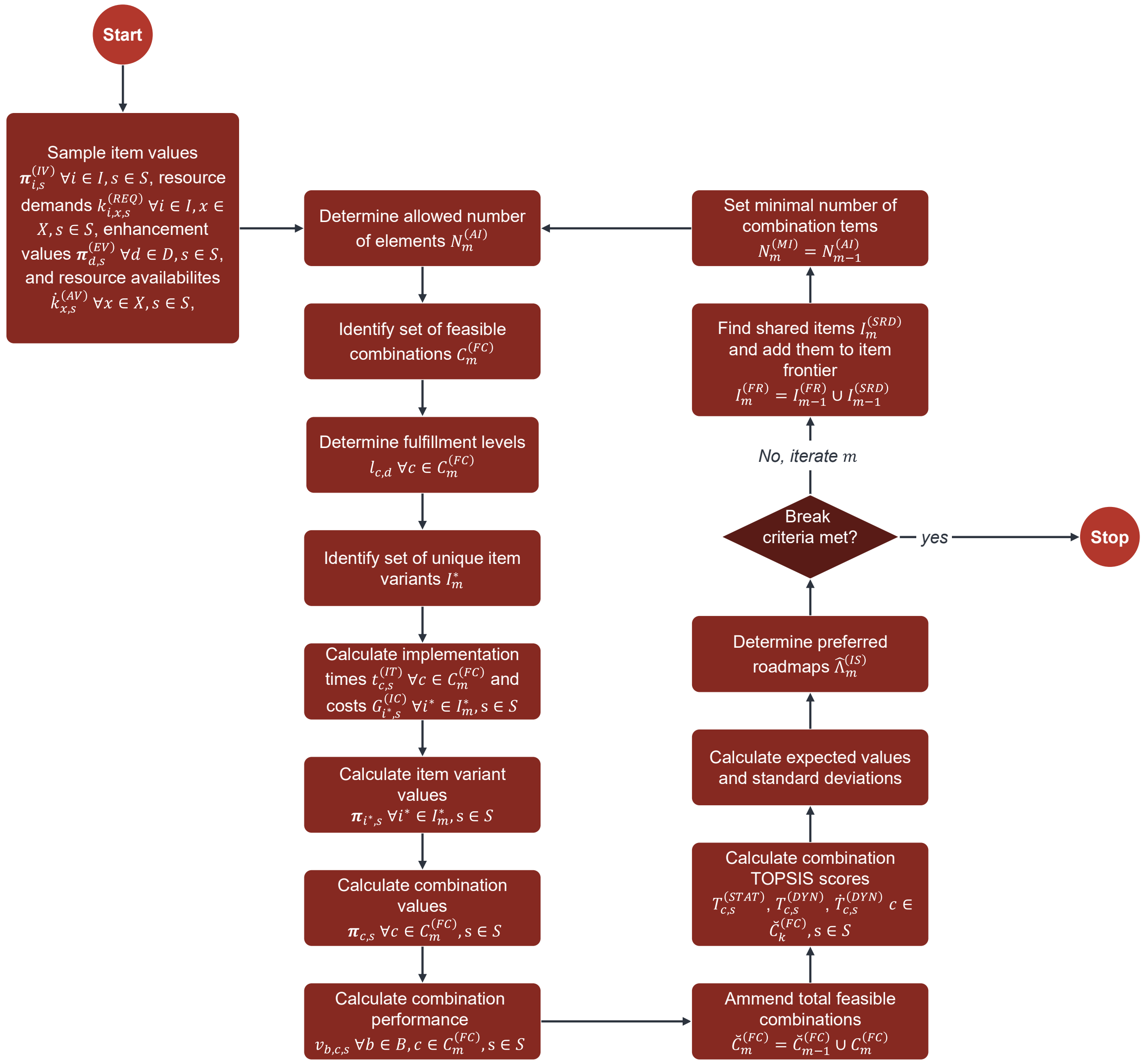

Figure A 11: Algorithm to Determine Implementation Roadmaps

Inputs & Sampling

Two conduct the priority assessment, several inputs are required. The objectives of the organisation $b \in B$ and their weights w_b need to be determined. For this an adapted pairwise comparison can be used. The resources for implementation $x \in X$, along with corresponding availability distributions $\tilde{\dot{k}}_x^{(AV)} = \left(\dot{k}_x^{(AV,MIN)}, \dot{k}_x^{(AV,MOD)}, \dot{k}_x^{(AV,MAX)}\right)$ and resource cost distributions $\tilde{g}_x^{(IMP,RES)} = \left(g_x^{(IMP,RES,MIN)}, g_x^{(IMP,RES,MOD)}, g_x^{(IMP,RES,MAX)}\right)$ have to be defined. A selection of items $i \in I^{(II)}$ from which the priority assessment choses have to be identified as specified in 4.5.2.3. For each item, a distribution function of resource demands $\tilde{k}_{i,x}^{(REQ)} = \left(k_{i,x}^{(REQ,MIN)}, k_{i,x}^{(REQ,MOD)}, k_{i,x}^{(REQ,MAX)}\right)$ is determined for the resources $x \in X$. Additionally, an item parameter distribution $\tilde{\pi}_{i,o} = (\pi_{i,o}^{(MIN)}, \pi_{i,o}^{(MOD)}, \pi_{i,o}^{(MAX)})$ is defined[92]. These values are used to calculate the benefits as defined in Appendix A5.1. For items on the data acquisition or base level, quality fulfilment values $p_{i,q}$ for a set of quality criteria $q \in Q^{(QLT)}$ are specified. A set of categorical dependencies $d \in D^{(CAT)}$ and a set of enhancing dependencies $d \in D^{(ENH)}$ are defined with exactly one dependent item $i_d^{(DEP)}$ and a set of $I_d^{(DEP)}$ dependency fulfilling items. For the enhancing dependencies, quality requirement $p_{q,d}^{(REQ)}$ and satisfaction $p_{q,d}^{(SAT)}$ levels are defined, along with quality criteria weights $w_{q,d}$. Finally, enhancing parameter distributions $\tilde{\pi}_{d,o} = (\pi_{d,o}^{(MIN)}, \pi_{d,o}^{(MOD)}, \pi_{d,o}^{(MAX)})$ are also specified for the enhancing dependencies.

In the beginning of the process, all these values are initially sampled.

Feasible Combinations

The set of feasible combinations $C^{(FC)}$ is determined as all unique item combinations c for which all categorical dependencies $d \in D^{(CAT)}$ of items $i_1, i_2 \in I$ are fulfilled:

$$\sum_{i_1 \in I} \sum_{d \in D} a_{c,i_1} r_{i_1,d} \left(1 - \max_{i_2 \in I}\left(a_{c,i_2} e_{d,i_2}\right)\right) = 0 \mid a_{c,i} = \begin{cases} 1 & , i \in I_c \\ 0 & , i \notin I_c \end{cases}, \quad \forall c \in C^{(CF)} \qquad \textit{Equation A 74}$$

Here I_c denotes all items that are part of combination c. $r_{i_1,d} = 1$ if i_1 depends on d and 0 otherwise and $e_{d,i_2} = 1$ if i_2 fulfils d and 0 otherwise.

For the iterative procedure, the number of independent items $N_c^{(II)}$ in a combination $c \in C_m^{(FC)}$ in each iteration m is bounded by a minimum number of items $N_m^{(MI)}$ and a maximum number of items $N_m^{(AI)}$

$$N_m^{(MI)} \leq N_c^{(II)} \leq N_m^{(AI)} \; \forall c \in C_m^{(FC)} \forall m \in M \qquad \textit{Equation A 75}$$

$N_m^{(MI)}$ is defined as

[92] In these distributions some values are left out, for example, items on the data acquisition or base level do not have any contributions to the benefits outside of costs.

$$N_m^{(MI)} = \begin{cases} 1 & , m = 1 \\ N_{m-1}^{(AI)} & , m > 1 \end{cases}$$ *Equation A 76*

$N_m^{(AI)}$ is chosen to limit the number of feasible combinations to be computed. A suitable value can be chosen using an estimator of the number of feasible combinations $N^{(EFC)}$:

$$N^{(FC,MAX)} \leq \alpha^{N_m^{(ACD)}} \binom{N^{II} - N_m^{(FR)}}{N_m^{(AI)} - N_m^{(FR)}} := N^{(EFC)}$$ *Equation A 77*

Where $N^{(FC,MAX)}$ is the limit of computable feasible combinations per iteration, $N_m^{(ACD)}$ is the number of possibly active categorical dependencies, α is an empirical reduction factor[93], N^{II} is the total number of implementation items, and $N_m^{(FR)}$ is the number of items that are part of the current iterations frontier. The items in this frontier $I_m^{(FR)}$ are active in every combination $c \in C_m^{(FC)}$:

$$I_m^{(FR)} = I_{c,m} \cap I_m^{(FR)} \; \forall \in C_m^{(FC)} \forall m \in M$$ *Equation A 78*

The frontiers are determined by the items chosen in every roadmap of the previous iteration:

$$I_m^{(FR)} = I_{m-1}^{(FR)} \cup \left(\bigcap_{\hat{\lambda} \in \hat{\Lambda}_{m-1}^{(IS)}} I_{\hat{\lambda}} \right) \forall m \in M/\{1\}$$ *Equation A 79*

This way, the algorithm can efficiently cover the space of feasible combinations while ensuring the solutions are globally optimal in most cases[94].

Enhancing Dependencies

Enhancing dependencies improve the benefits of an application item if they are fulfilled. The fulfilment level $l_{c,d}^{(COM)} \in (0,1)$ of an enhancing dependency $d \in D^{(ENH)}$ is specified as

$$l_{c,d}^{(COM)} = \max_{i \in I_c} \left(l_{i,d}^{(ITM)} \right) \forall c \in C^{(CF)}$$ *Equation A 80*

[93] In practice a value of $\alpha = 0.9$ has proven to be suitable.

[94] The only exception to this occurs, when a set of items would in combination yield a higher performance than other items, but the required number of items eclipses the allowed number. Then the lower performing single items may be added to the frontier and solutions containing the set would not be considered if they did not include the lower performing single items. This problem can be mitigated by maximising the number of considered items per iteration.

Where $l_{i,d}^{(ITM)}$, the fulfilment level of enhancing dependency d by item i, which is specified as

$$l_{i,d}^{(ITM)} = \sum_{q \in Q^{(QUL)}} w_{q,d} \min\left(\max\left(\frac{p_{q,i} - p_{q,d}^{(REQ)}}{p_{q,d}^{(SAT)} - p_{q,d}^{(REQ)}}, 0 \right), 1 \right) \quad \textit{Equation A 81}$$

with the weights $w_{q,d}$ associated with quality criteria $q \in Q^{(QUL)}$ adhering to $\sum_{q \in Q^{(QUL)}} w_{q,d} = 1 \forall d \in D^{(ENH)}$. $p_{q,i}$ refers to the fulfilment level of i on q and $p_{q,d}^{(REQ)}$ and $p_{q,d}^{(SAT)}$ specify the requirement and satisfaction level of q for d, with $p_{q,d}^{(SAT)} \geq p_{q,d}^{(REQ)}$.

Benefit Assessment

For each objective type b a specific performance function $f_b^{(PER)}\left(\boldsymbol{\pi}_b^{(FIX)}, \boldsymbol{\pi}_b^{(ENH)}\right) = y_b$ is defined, in which $\boldsymbol{\pi}_b^{(FIX)}$ denotes the vector of parameters only specified by the items and $\boldsymbol{\pi}_b^{(ENH)}$ denotes the vector of parameters affected by items and enhancing dependencies. The overall weighed performance $v_{b,c}$ of a combination c on a benefit type b can then be expressed as

$$v_{b,c} = w_b \sum_{i \in I_c} f_b^{(PER)}\left(\overbrace{\boldsymbol{\pi}_{b,i}^{(FIX)} + \sum_{d \in D_i^{(ENH)}} l_{c,d}^{(COM)} \acute{\boldsymbol{\pi}}_{b,d}^{(ENH)}}^{\boldsymbol{\pi}_{b,i^*}} \right) \quad \textit{Equation A 82}$$

, where w_b is the weight associated with b, $\boldsymbol{\pi}_{b,i}^{(FIX)}$ are the values associated with an item i, $d \in D_i^{(ENH)}$ is the set of dependencies enhancing i, and $\acute{\boldsymbol{\pi}}_{b,d}^{(ENH)}$ is the parameter vector associated with dependency d.

To efficiently calculate the combination values, item variants $i^* \in I_m^*$ are introduced containing all uniquely enhanced items in $C_m^{(FC)}$. Then the item variant specific values $\boldsymbol{\pi}_{b,i^*}$ can be computed without redundancy and broadcasted to $v_{b,c}$ for all $i^* \in I_c^*$.

TOPSIS

Using the weighed performance scores for each item on each benefit criterion, the separations from the positive and negative ideal S_c^+ and S_c^- are determined as

$$S_c^+ = \sqrt{\sum_{b \in B} \left(v_b^+ - v_{b,c}\right)^2} \quad \textit{Equation A 83}$$

and

$$S_c^- = \sqrt{\sum_{b \in B} \left(v_{b,c} - v_b^-\right)^2} \qquad \textit{Equation A 84}$$

with

$$v_b^+ = \max_{c \in C^{(CF)}} v_{b,c} \qquad \textit{Equation A 85}$$

and

$$v_b^- = \min_{c \in C^{(CF)}} v_{b,c} \qquad \textit{Equation A 86}$$

Using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), a utility score can be calculated for each combination:

$$T_c^{(STAT)} = \frac{S_c^-}{S_c^+ + S_c^-} \qquad \textit{Equation A 87}$$

Dynamic TOPSIS

When applying a Monte-Carlo-Simulation (MCS) this score can be calculated for every sample n, such that the expected TOPSIS score $\mathbb{E}\left[T_c^{(STAT)}\right]$ is:

$$\mathbb{E}\left[T_c^{(STAT)}\right] \approx \frac{1}{N} \sum_{n=1}^{N} T_{c,n}^{(STAT)} \qquad \textit{Equation A 88}$$

and the standard deviation $\varsigma\left[T_c^{(STAT)}\right]$ is:

$$\varsigma\left[T_c^{(STAT)}\right] \approx \sqrt{\frac{1}{N} \sum_{n=1}^{N} \left(T_{c,n}^{(STAT)} - \mathbb{E}\left[T_c^{(STAT)}\right]\right)^2} \qquad \textit{Equation A 89}$$

Using the resources available, the required implementation time $t_c^{(IMP)}$ is defined as

$$t_c^{(IMP)} = \max_{x \in X^{(IMP)}} \left(\frac{k_{c,x}^{(REQ)}}{\dot{k}_x^{(AV)}}\right) \qquad \textit{Equation A 90}$$

, where $k_{c,x}^{(REQ)}$ is the required implementation capacity of resource x for c and $\dot{k}_x^{(AV)}$ the availability rate of that resource. $k_{c,x}^{(REQ)}$ is calculated as follows:

$$k_{c,x}^{(REQ)} = \sum_{i \in I_c} \left(k_{i,x}^{(REQ)}\right) \ \forall x \in X \qquad \textit{Equation A 91}$$

For the implementation time, expected value $\mathbb{E}\left[t_c^{(IMP)}\right]$ and standard deviation $\varsigma\left[\mathrm{t}_c^{(IMP)}\right]$ can be computed analogously. Using the implementation time, the utility increase rate $\dot{T}_c^{(STAT)}$ can be expressed as

$$\dot{T}_c^{(STAT)} = \frac{T_c^{(STAT)}}{t_c^{(IMP)}} \qquad \text{Equation A 92}$$

, which the organisation should try to maximise. In combination with the enhancing dependencies, which represent synergies between implementation items, maximising $\dot{T}_c^{(STAT)}$ would favour large combination sets. To amend this and better specify the order at which items should be implemented, the utility value can be dynamically discounted:

$$T_c^{(DYN)} = \frac{T_c^{(STAT)}}{\left(\frac{\mathrm{t}_c^{(IMP)}}{t^{(IMP,REF)}}\right)^{e^{(DYN)}}} \mid e^{(DYN)} \in \mathbb{R}^+ \qquad \text{Equation A 93}$$

, where $e^{(DYN)}$ denotes the immediacy preference and $t^{(IMP,REF)}$ is the reference realisation time. Then the dynamic utility increase rate $\dot{T}_c^{(DYN)}$ follows:

$$\dot{T}_c^{(DYN)} = T_c^{(STAT)} \frac{{t^{(IMP,REF)}}^{e^{(DYN)}}}{{t_c^{(IMP)}}^{1+e^{(DYN)}}} \qquad \text{Equation A 94}$$

Pareto Front of Combinations

Using the optimistic dynamic utility increase rate $\dot{T}_c^{(DYN,OPT)} = \mathbb{E}\left[\dot{T}_c^{(DYN)}\right]$ and the pessimistic dynamic utility rate $\dot{T}_c^{(DYN,PES)} = \mathbb{E}\left[\dot{T}_c^{(DYN)}\right] - \varsigma\left[\dot{T}_c^{(DYN)}\right]$, a Pareto front of combinations P_0 can be determined. Depending on the risk preference of the organisation, the most suitable combination can be chosen. To determine the preferred combination, distance-based weighing may be applied. Here the value of a combination T_c is expressed as:

$$T_c = \sqrt[\rho]{\left|\left(w^{(OPT)} r_c^{(OPT)}\right)^\rho + \left(w^{(PES)} r_c^{(PES)}\right)^\rho\right|}, \rho \in (1,\infty), w^{(OPT)} + w^{(PES)} = 1 \qquad \text{Equation A 95}$$

where ρ denotes the distance norm, $w^{(OPT)}$ and $w^{(PES)}$ describe the weight given to the estimated value and the deviation respectively, and $r_c^{(OPT)}$ and $r_c^{(PES)}$ describe the unidimensional distance of the combination c from the ideal point. The risk preference ratio of an organisation may be described as the ratio between $w^{(OPT)}$ and $w^{(PES)}$:

$$R = \frac{w^{(PES)}}{w^{(OPT)}} \qquad \text{Equation A 96}$$

The ratio can be transformed to a preference angle θ using:

$$\theta = \arctan\left(\frac{w^{(PES)}}{w^{(OPT)}}\right) = \arctan(R) \qquad \text{Equation A 97}$$

The natural risk preference angle θ_c of a combination c can be expressed as:

$$\theta_c = \arctan\left(\frac{{r_c^{(OPT)}}^{\rho}}{{r_c^{(PES)}}^{\rho}}\right)$$ *Equation A 98*

By finding the crossover points between the combinations which are part of the Pareto front, preference ranges can be established for the combinations. Using

$$\sqrt[\rho]{\left|\left(w^{(OPT)}r_{c_1}^{(OPT)}\right)^{\rho} + \left(w^{(PES)}r_{c_1}^{(PES)}\right)^{\rho}\right|} = \sqrt[\rho]{\left|\left(w^{(OPT)}r_{c_2}^{(OPT)}\right)^{\rho} + \left(w^{(PES)}r_{c_2}^{(PES)}\right)^{\rho}\right|}$$ *Equation A 99*

The crossover preference angle $\theta_{c_2 \to c_1}$ is established as

$$\theta_{c_2,c_1} = \arctan\left(\sqrt[\rho]{\frac{{r_{c_1}^{(OPT)}}^{\rho} - {r_{c_2}^{(OPT)}}^{\rho}}{{r_{c_2}^{(PES)}}^{\rho} - {r_{c_1}^{(PES)}}^{\rho}}}\right)$$ *Equation A 100*

The resulting preference regions are described with a set of crossover angles which fulfil:

$$\theta_{c_j,c_i} < \theta_{c_j,c_k} \forall c_k \in P, j > k > i$$ *Equation A 101*

for every combination of $c_i, c_j \in P$. In Figure A 12 this is demonstrated for $\rho = 1$, the so-called Manhattan norm. The figure highlights, that for $\rho < \infty$ concave regions of the Pareto front, combinations can be omitted. For each crossover point, an iso-value line can be determined as shown in the figure. The result for the Manhattan norm is equivalent to a linear weighing of different options.

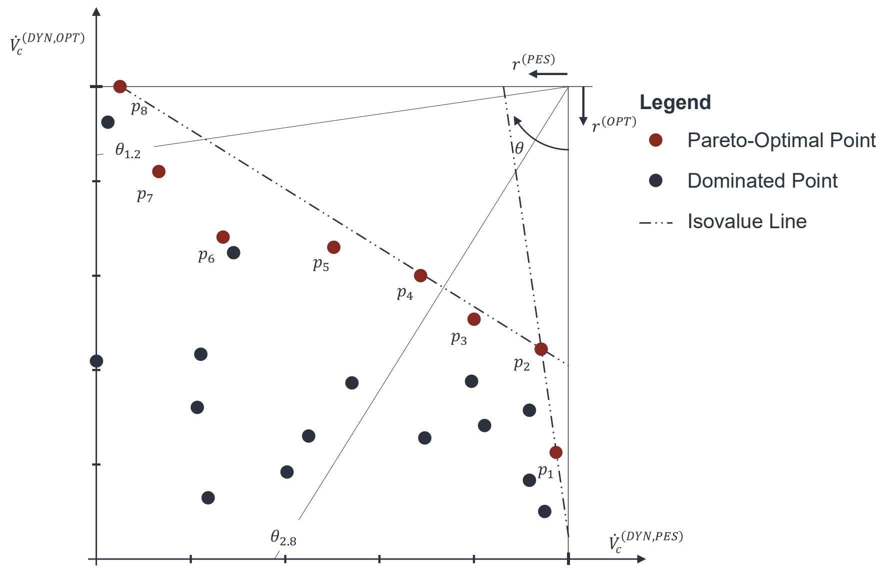

Figure A 12: Pareto Risk Profile Weighed with Manhattan Norm

Figure A 13 shows a comparison of the same Pareto front assessed using three different norms, Manhattan, $\rho = 1$, Euklidian, $\rho = 2$, and Maximum norm, $\rho = \infty$. Whereas the Manhattan norm only considers points p_1, p_2, and p_8, the Euklidian norm also recognises p_3, p_4, and p_5. Using the maximum norm, naturally all points on the Pareto front are considered. In the following the Euklidian norm is employed to assess the preference ranges, as it can identify the attractiveness of a solution well and matches decision maker intuition. This results in a set of preferred combinations $c_i \in P'$ and a corresponding set of preference angle ranges $\Theta_{c_i} = \left(\theta_{c_i}^{(LEF)}, \theta_{c_i}^{(RIG)}\right) := \left(\theta_{i-1,i}, \theta_{i,i+1}\right)$, where $\theta_{0,1} = 0$ and $\theta_{N_\Theta - 1, N_\Theta} = \frac{\pi}{2}$.

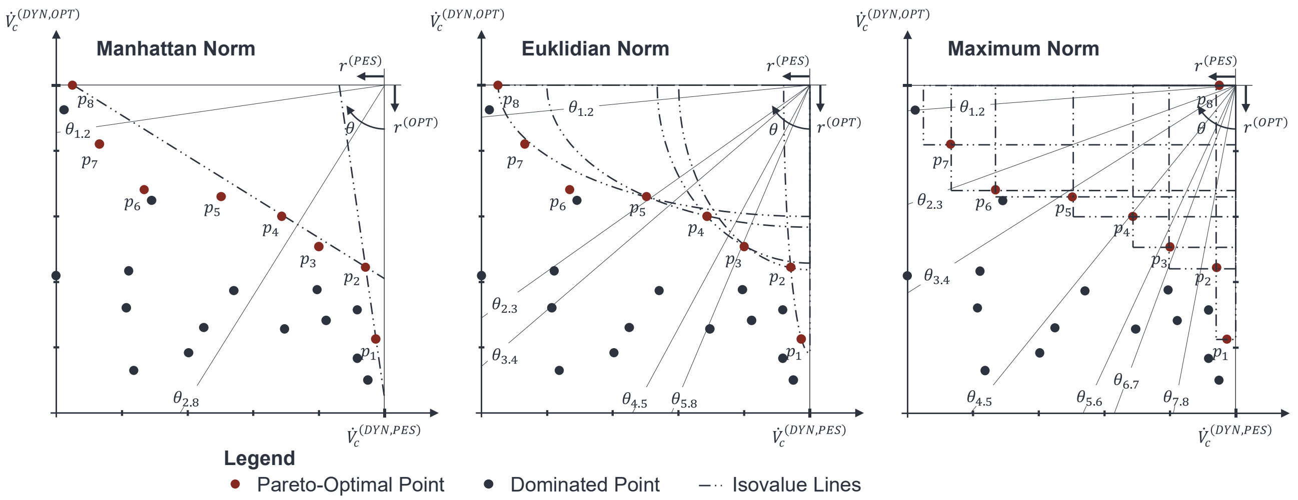

Figure A 13: Pareto Risk Profile with Three Different Weighing Norms

To not only consider a single implementation step but create a chain of steps an iterative procedure can be applied. It uses the above-described procedure but limits the considered set of combinations based on previously found successors and predecessors if they exist. To do so, the set of feasible combinations $C^{(FC)}$ is reduced to the set of feasible subsequent combinations $C_{c_0}^{(SC)}$ for a given initial combination c_0. The combinations of this set must fulfil the following conditions:

$$a_{c_0,i} \leq a_{c,i} \forall c \in C_{c_0}^{(SC)}, i \in I$$ *Equation A 102*

and

$$\mathbb{E}\left[T_{c_0}^{(STAT)}\right] \leq \mathbb{E}\left[T_c^{(STAT)}\right] \forall c \in C_{c_0}^{(SC)}$$ *Equation A 103*

Similarly, the set of feasible predecessor combinations $C_{c_2}^{(PC)}$ for c_2, starting from $C^{(FC)}$ is determined by:

$$a_{c,i} \leq a_{c_2,i} \forall c \in C_{c_2}^{(PC)}, i \in I$$ *Equation A 104*

From the limited set of feasible combinations C'_{c_0,c_2} a set of preferred combinations P'_{c_0,c_2}can be deducted.

Iterative Roadmap building

This process can then be applied recursively. The procedure is initiated with a fill-search without predecessor or successor resulting in P'_0. Then a backfill operation is conducted for every $c \in P'_0$. The resulting $P'_{0,c}$ is limited to the limited set of preferred combinations $P''_{0,c}$for which Θ'_{c_i}=$\Theta_{c_i} \cap \Theta_c \neq \emptyset | \forall c_i \in P''_{0,c}$. After the backfilling, a forward fill is conducted in the same manner for each chain of combinations $u \coloneqq [c_1, \dots, c_N]$ resulting from the backfill. Finally, neighbouring chains u_i, u_j with $\theta_{u_i}^{(RIG)} = \theta_{u_j}^{(LEF)}$, for which $u_i = u_j$ is true, are joint. For each c_i found in either the back or forward filling operation a new back and forward filling cycle is started, until $P''_{c_{i-1},c_i} = \emptyset$ or $P''_{c_i,c_{i+1}} = \emptyset$, respectively[95]. After each forward filling operation neighbouring chains of combinations are merged. This

[95] Here c_{i-1} refers to the current predecessor within the active chain and c_{i+1} refers to the current successor to c_i in the active chain.

sequence search process is illustrated in unidimensional form, disregarding the risk preference in Figure A 14.

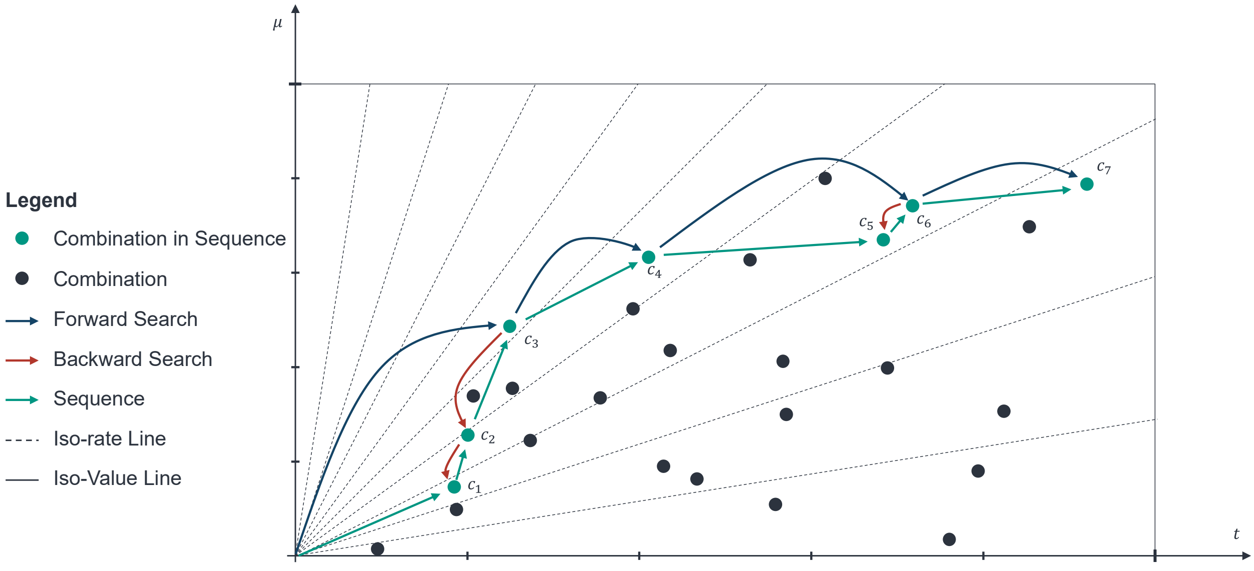

Figure A 14: Unidimensional Sequence Search

Figure A 15 portrays a single backwards search step in detail, where only a limited set of combinations, which are predecessors to c_1 are considered.

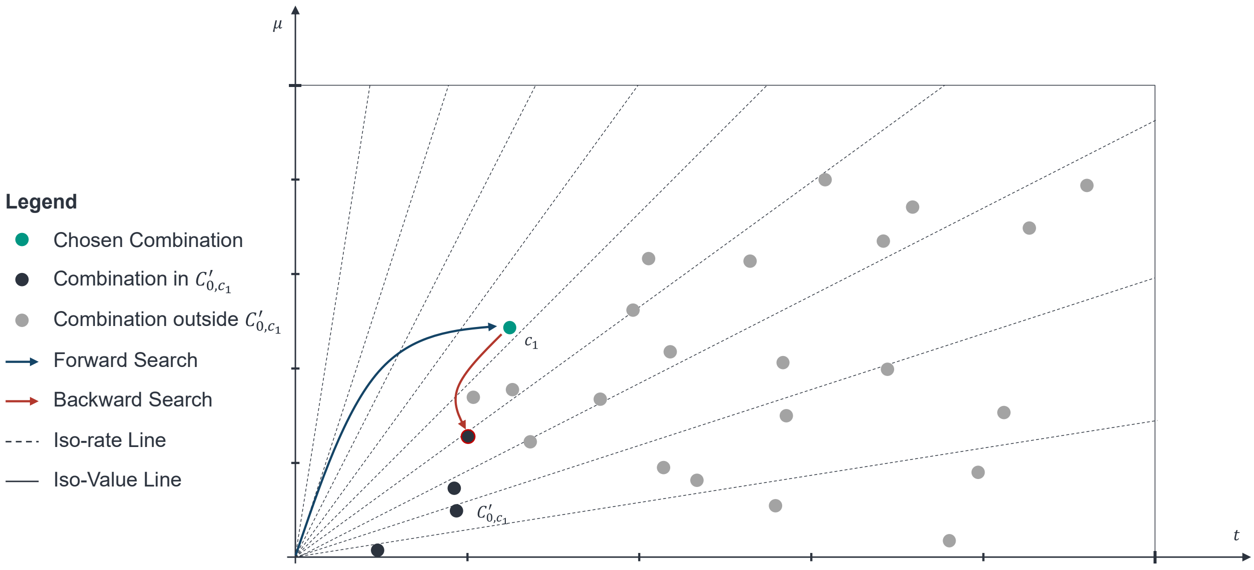

Figure A 15: Backward Search Step in Unidimensional Sequence Search

To realise this process a recursive filling function for roadmaps is implemented as shown in Figure A 16. This function fills a slot between two previously successive combinations $c^{(PRE)}$ and $c^{(SUC)}$ by first conducting one pareto search on the set between them and then recursively calling itself to fill the spaces before and after the new configuration $c^{(NEW)}$. Whenever the roadmap search yields multiple results, the roadmap is split along the value preference ranges.

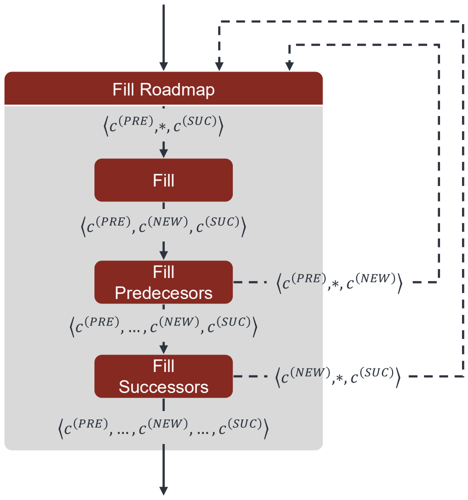

Figure A 16: Recursive Roadmap Filling Function

The result of this process is a portfolio of Pareto optimal implementation roadmaps, from which a decision maker may chose depending on their risk preference.

A6 Automated Planned Volume Allocation Design

The following analyses the design of the Automated Planned Volume Allocation (APVA) DSS. It is described in … and used as a starting point for the authors own DSS development. The author was however not primary responsible for its development. In the following analysis modelling decisions made are investigated and compared to results the systematic DSS development process introduced in 4.2.3 would suggest. These deliberations should aid the assessment of the systematic design process, as its ability to both find similar conclusions to those determined by expert model developers and the capability to highlight possible amendments is demonstrated. However, this cannot be seen as a fully objective test, as the author knows the resulting APVA tool and may thus be influenced by previous knowledge.

The APVA tool is designed to support the organisations Planned Volume Allocation (PVA) process. This process determines at which sites and lines ordered volumes and order forecasts should be allocated. This decision is made for each product produced at multiple sites in so called International Production Networks (IPN). An IPN covers a single production echelon of a GPN for one specific product. For not directly customer facing production echelons, separate IPNs are considered, that view the subsequent IPNs as customers. In accordance with the allocation decision, decisions on investments into new lines and line features, as well as line decommissioning and several auxiliary decisions are made. This process serves as a central basis for several subsequent planning processes.

Figure A 17 portrays the existing PVA process performed primarily by the divisional production coordination and the production network planning assigned to specific IPNs. Other departments play a supporting role in the process as portrayed in Table A 20.

The process starts with *creating a sales-PVA data transfer* for the production network planning. Here both PVA master data and sales and demand forecasts are considered.

Next the main step follows, the *allocation of planned volumes* according to several constraints, like specific customer request, premises of the business unit, technical capabilities for products and locations, different location types, the planning information from logistics, and the previous year’s PVA results. This step involves a complex consideration of the constraints and includes a very high number of decision variables due to the number of considered orders.

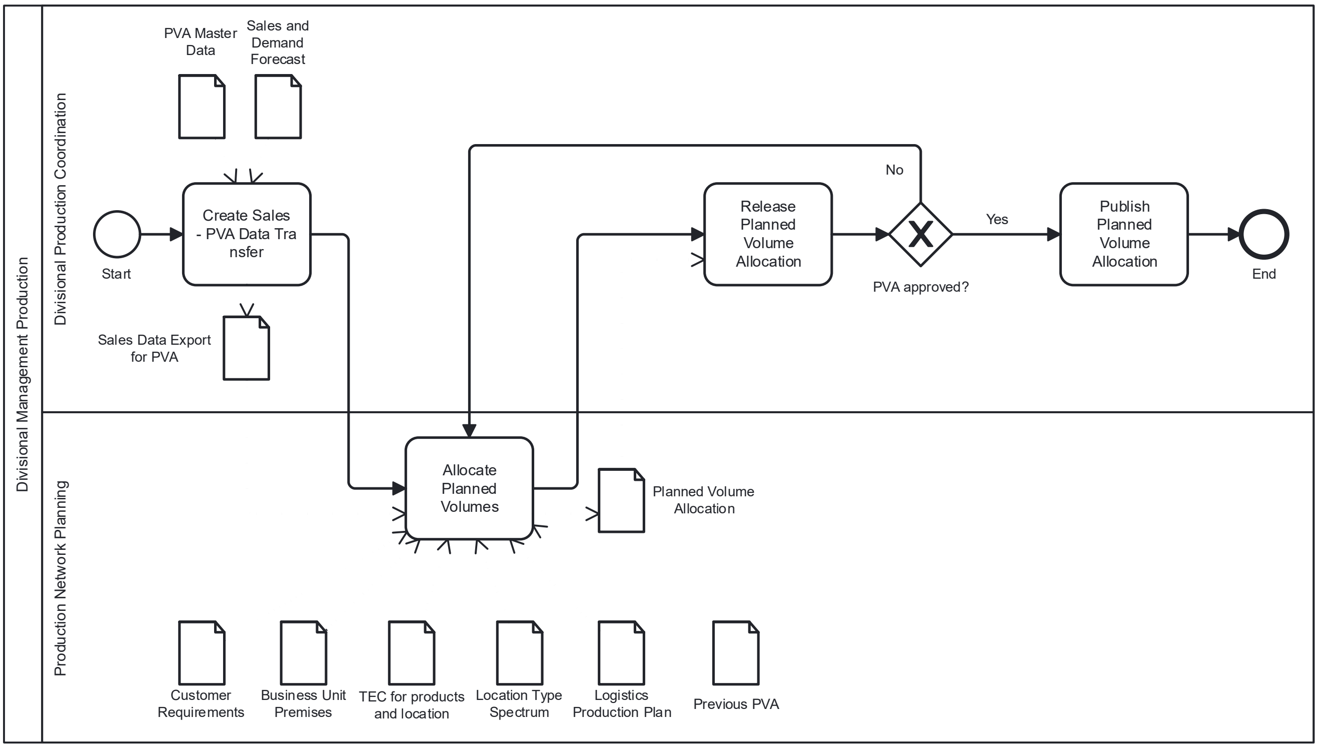

Figure A 17: Existing Planned Volume Allocation Process

Subsequently, the *PVA is released* for decision by the appointed allocation approver. When approval is successful it passes on to *publishing* to other organisational functions and putting decisions into action. If the PVA is rejected, it is reiterated by the production network planning.

Table A 20: Responsibility Assessment Matrix for PVA Process

Process	**Divisional Executive Management**	**Divisional Production Coordination**	**Production Network Planning**	**Production Network Leader**	**Plant Network Contact**	**Allocation Approver**	**Allocation Release Approver**
Create Sales-PVA Data Transfer		Responsible					
Allocate Planned Volumes		Support	Responsible		Support	Approve	
Release Planned Volume Allocation	Support	Responsible		Support			Approve
Publish Planned Volume Allocation		Responsible	Support				

In this process, especially the allocation step can be supported by DSS to address the complexity of the decision. In the following, the design of APVA, which addresses this process step is investigated. Whereas Appendix A7 covers every step of the design process for LTPA in detail, the following only summarises the main steps and highlights agreements and differences between the implemented design and suggested results.

A6.1 Decision Type Analysis

The first phase of the design process is decision type analysis which consists of three steps, establishing the time horizon, selecting major system elements, and lastly determining the desired AC.

For the time horizon, the organisational characteristics have to be taken into account. They are shown in detail and discussed in Appendix A7.1 and Table A 24. Next the lead decision variable that determines the time horizon is identified. The lead decision variable in PVA is the set-up of production resources, in this case lines, which takes up to two years. In addition, other changes to production resources, releases and certifications and work-time models are considered as decision variables. This leads to a plausible shortest time horizon of 4 years. In practice an 8-year time horizon is chosen, which accommodates the subsequent decisions that PVA supports. For a 4-year time horizon a choice of quarter years as periods would have been sensible but to limit the complexity in the 8-year case the chosen half-year periods are pragmatic.

Next the major system elements are selected. This involves a consideration of objectives pursued in APVA. The primary objective is to lower costs of production in the form of net present costs, but several secondary objectives should be considered. Those are, volume and sourcing flexibility, robustness, global warming potential and job security. The considered domains primarily include production, logistics, and sales. With this, the major system elements can be deduced, which describe the decisions to be made. Those include all changes to production resources, transportation modes and routes, worker time models, allocation of product variants and order quantities, and determination of necessary releases for sites and lines. The result of this step is in alignment with the implementation.

The final step of the first phase is the deduction of the desired analytical capability. For this the external influences are first detailed. The most important influences based on the analysis are (i) customer composition, (ii) economically driven demand, (iii) labour, (iv) capital, and (v) material costs, (vi) transportation costs, (vii) currency fluctuations, and (viii) duties. Whereas the first two are explicitly considered in APVA to create scenarios, the latter are considered deterministic. This limitation is primarily pragmatic, but an extension of APVA to consider those influences may be beneficial. In the next step, the DMC for APVA is structured. It consists primarily of the responsible network planners and the divisional manufacturing coordination as shown in Table A 20. Several other supporting functions assist the process and require corresponding explanation. With this information, the desired AC for APVA can be assessed. Table A 21 shows this assessment which results in a 0.37 score for APVA indicating a high AC. This is driven by the relative system linearity, the high number of decision variables, high frequency of similar decisions, decision routine, and quantifiability of objectives. This result agrees with the implementation of APVA which may characterised as a fully prescriptive model.

Table A 21: Assessment of Desired AC for APVA

Decision Situation Characteristic		**Weight**	**Value**	**Flow**	**Description**
DC01	System Linearity	0.08	5	0.05	High: Consideration is primarily cost focused, and interactions are mostly linear.
DC02	Number of Decision Variables	0.10	6	0.10	Very High: Multitude of Orders combined with other decisions creates a very high number of decision variables.
DC03	System Expertise	0.02	5	0.00	High: IPN planners are very familiar with the specific planned network and products.
DC04	Uncertainty	0.06	4	-0.01	Moderately high: Primarily affected by market volatility and logistical changes.
DC05	Decision Frequency	0.10	5	0.06	High: Regular planning intervals, additional non planned decisions, several planning instances.
DC06	Decision Routine	0.08	5	0.05	High: Well described decision process and goals, with some deviations due to specific considerations.
DC07	Development Capabilities	0.04	5	0.00	High: Good availability of developers.
DC08	Perspective Diversity	0.03	3	0.01	Moderately low: Focus on one product family and only considering production and logistics.
DC09	Achievable Accuracy	0.06	5	0.04	High: Available data and models allow for good accuracy.
DC10	Objective Quantifiability	0.10	5	0.06	High: The primary objective is cost which is relatively easy to quantify.
DC11	Data Acquisition Intensity	0.06	3	0.01	Moderately low: Most data required is readily available, but line capabilities and logistic costs are somewhat challenging to access.
DC12	Time Horizon	0.10	4	-0.02	Moderately high: Relatively long-time horizon due to investments and subsequent planning processes.
DC13	Decision Time	0.10	3	0.02	Moderately low: Given process only allows for relatively short decision times of two weeks.
DC14	Computing Capabilities	0.01	5	0.00	High: Good availability of computing capabilities.
DC15	Desired Explainability	0.04	3	0.01	Moderately high: Major decisions need to be explainable, decisions on orders are not as crucial to be explained.
DC16	Model Expertise	0.01	4	0.00	Moderately high: Model users are well educated and familiar with simple predictive and prescriptive models.
	Sum	**1**		**0.37**	

A6.2 Method Composition

The second phase analyses the methods applied in APVA. This phase includes two steps, procedural factor determination and DSS method architecture. Both are discussed in the following.

Procedural Factor Determination

For procedural factor particularisation, objectives, external influences, decision variables and the decision process need to be taken into account.

The objectives can be specified in more detail. The cost objective is calculated as net present costs and includes fix costs for line activities, variable line operation costs with over- and undercapacity costs, material costs, logistic costs including bound capital, license costs for customer releases, and investment costs for new lines and feature upgrades. Flexibility in terms of volume and sourcing is considered as a condition for selected orders. Global warming potential is transformed to a cost term. In APVA those costs are only considered for logistics, even though a broader consideration may be helpful. Job security is considered through the BU premises that enforce specific sites to have predetermined volume shares.

External influences include market side effects, which can be considered stochastically, by altering the necessary production volumes per order. This way one of the largest influences is considered. Changes in the other relevant external factors are only considered as part of manually determined planning scenarios not by using a generation methodology in APVA. The DSS design process suggests, that especially for material and logistic cost fluctuations and currency changes, corresponding automatic scenario generation may be suitable. Duties on the other hand require specific system knowledge so a consideration as part of manual exploration as implemented in APVA seems apt.

Next, the decision variables are allocated to different sets. The corresponding result for APVA is shown in Figure A 18. It shows that the site premises, production demands and produced products is given as an input. The users determine the possible new lines and line upgrades manually as well as associated costs. The other results are then determined prescriptively. Notably, the results contain some inconsequential decisions on exact order line allocations, transportation volumes, and release acquisitions, which are revisited in subsequent decisions. Overall, the resulting decision variable allocation is in agreement with what the systematic development methodology would suggest.

Lastly the decision process needs to be designed in accordance with the conceptualised DSS. The decision process is very formalised, can be iterative, and is part of a hierarchical schedule. As the DSS design is focused on a specific step in the process depicted in Figure A 17, relatively little needs to change. The integration between sales and production network planning needs to be tighter to derive scenarios for sales. Also, APVA requires detailed logistic costs, so the logistic function needs to be integrated more tightly as well. These are changes that the implemented APVA solution also specifies, so design process and actual implementation are in agreement.

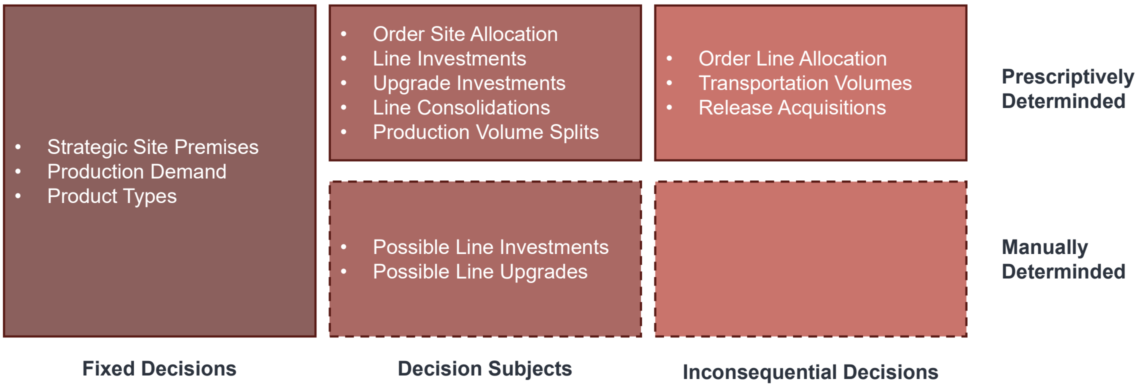

Figure A 18: Decision Variable Sets in APVA

DSS Method Architecture

In the following the method selection for APVA is discussed based on the previously defined characteristics.

The predictive method ideally supports prescriptive decision-making with a large number of decision variables. It should also reflect the stochasticity introduced by sales scenarios. The most suitable choice is thus, stochastic, mixed integer linear modelling, especially since the system behaviour is predominantly linear. This is also what is chosen in the implementation. For decision selection, post optimality analysis could be applied to find out more about the reasons behind the predictive models results. However, this is largely foregone in APVA, instead focusing on a manual analysis and use of the prescriptive results. As a configurative method, consequently mixed integer linear programming (MILP) should be and is used. Consequently, the scenario generation method for sales scenarios needs to automatically generate a selection of meaningful scenarios that do not exceed the computing capabilities of the stochastic MILP. The logical choice made in APVA is to create scenarios using Monte-Carlo Simulation and then using clustering to reduce the number of scenarios. As the resulting method already fulfils the desired AC level and interpolation for faster computing seems difficult due to the size of the decision space, no meta-modelling methods should be used, which agrees with the APVA implementation.

A6.3 Model Detailing

The last phase of the design process is model detailing. It involves the determination of requirements and restrictions and DSS specification.

Requirements & Restrictions Determination

In the following, behavioural and accuracy requirements and data, model, and computational restrictions are briefly discussed.

Noteworthy behavioural requirements are the representation of dynamic line ramp-ups, the ability to allow for dynamic overcapacity with additional costs, and fixing investment decisions in the four first planning periods.

In terms of accuracy, the investment and variable costs should be accurately reflected as well as actual capacity. Furthermore, the capabilities of production lines vis-à-vis product variants should be faithfully represented. Finally, the capacity of production lines and capacity demand of products should be accurately predicted.

Data requirements affect the investment costs for new lines and upgrades which can often only be estimated with limited accuracy. Logistics costs depend on the transportation volumes and can thus only be estimated in linearised form. Logistic costs are only available from region to region. Capabilities required for not yet introduced variants often needs to be estimated based on known variants.

The chosen implemented model also places specific limitations. Overcapacity and undercapacity costs can only be captured in linearised form. Closing and later reopening of lines is not possible. Existing lines or stations cannot change location. Inter-period storage cannot be considered.

Finally, computational restrictions apply. As the optimisation occurs on local clusters only 10 scenarios can be considered at the same time. Furthermore, only a single production echelon, corresponding to the definition of IPN can be computed at once due to the complexity induced by multiple process steps.

DSS Specification

In DSS specification, the abstraction level, the chosen model expression for system elements and delimitation criteria are determined. In the following, the essential aspects are discussed.

Several abstractions are applied. Order volumes are aggregated by unique combinations of period, customer, and product variant. Fixed and variant costs are considered per line without consideration for the source of costs. Lines are considered one for one distinct IPN definition and processing steps are not distinguished. Transport tasks are only distinguished by the pair of regions based on the data restrictions.

Several model expressions are chosen. Ramp-up curves are modelled using pre-parametrised OEE curves for new lines. Order volumes are considered as continuous, variables. Flexibility is implemented as a condition demanding, that orders are produced at more than one site.

The last aspect is delimitation. The considered network is delimited to one production echelon, in accordance with the IPN definition. Only costs directly related to operations are considered.

Many of the decisions made in this last step require deep knowledge of the model and its characteristic. This results in a relatively high bias, so that decisions cannot be evaluated by the author from an outside perspective. Nevertheless, the decisions made occur plausible when considered from the systematic DSS design perspective.

Overall, the systematic design process aligns in many aspects with the actual implementation, while suggesting some alternative solutions that would likely improve the resulting DSS.

A6.4 Data Demands of APVA

In the following, the data demands for APVA are analysed. This analysis is based on A_Bramey (2023), which was supervised by the author. The resulting demands are shown in Table A 22.

Table A 22: Data Demands for APVA

Model Element	Data Demand		Demand Type
Region	DD29	Regions	set
	DD30	Prescribed Volume Share	numerical
Site	DD01	Sites	set
	DD31	Site - Region	categorical
	DD32	Prescribed Volume Share	numerical
Customer	DD33	Customers	set
	DD34	Customer - Region	categorical
Line	DD35	Lines	set
	DD36	Possible Lines	set
	DD19	Line – Site Allocation	categorical
	DD37	Fixed Line Costs	numerical
	DD38	Variable Line Costs	numerical
	DD39	Variable Line Cost Change	numerical

Model Element	Data Demand		Demand Type
	DD40	Underutilisation Costs	numerical
	DD41	Overutilisation Costs	numerical
	DD42	Maximum Capacity	numerical
	DD43	Nominal Capacity	numerical
	DD44	Existing Features	categorical
	DD45	Feature Acquisition Costs	numerical
	DD46	Line OEE	numerical
Feature	DD47	Features	set
Order	DD48	Orders	set
	DD49	Order - Customer	categorical
	DD50	Order Volume per Period	numerical
	DD51	Fixed Allocation to Site in Period	categorical
	DD52	Flexible Order Designation	categorical
	DD53	Material Provision Costs per Site	numerical
	DD54	Existing Line Releases	categorical
	DD55	Existing Site Releases	categorical
	DD56	Line Release Costs	numerical
	DD57	Site Release Costs	numerical
	DD58	Required Features	categorical
	DD59	Line Specific Cycle Time	numerical
Event	DD60	Events	set
	DD61	Entry Likelihood per Period	numerical
	DD62	Order Volume Changes on Entry	numerical
Transport	DD63	Origin Region	categorical
	DD64	Destination Region	categorical
	DD65	Piecewise Logistic Costs	numerical

A7 Long-Term Planning Assistant Development

The following discusses the development of the DSS called Long-Term Planning Assistant (LTPA). LTPA is the result of the master's theses A_Bauer (2023), A_Steinkühler (2023), and A_Bolender (2024), which were supervised by the author of this work. The result of this development has been published in Benfer et al. (2024).

The overall objective of LTPA is to support decisions on the future strategic direction of the production sites, particularly concerning the allocation of product families and associated capacities of personnel and manufacturing area. A corresponding process for these decisions, called Long-Term Planning Manufacturing (LTP-M), already exists at the automotive supplier. Thus, the design process of LTPA is a brownfield process, where several existing information can be used, but existing process boundaries also have to be observed.

This existing LTP-M process is depicted in Figure A 19. The majority of the process is performed by the central divisional manufacturing coordination, with the involvement of the divisional executive management and the relevant production sites. Other departments also play a supporting role, as illustrated in Table A 23.

The process starts with *data preparation*, where relevant data like the PVAs of considered networks are used, as well as a forecast of the factor cost developments, divisional strategic premises, and the result of the previous process. This data is used to create an LTP-M template, which is distributed to relevant production sites to be filled out.

Next, the production sites determine their available area and personnel capacity, as well as the expected value added based on necessary investments. This data is then provided to the manufacturing coordination in the process step *process request and provide feedback*.

The *feedback is received* and optionally *checked for plausibility* based on the observed criticality and divisional policies. Depending on the divisional requirements, the results of this process are *consolidated and visualised*. Next the results are presented to the executive management. If adjustments are necessary, the executive management *develops scenarios* for adjustment, which are effectively decision alternatives. Subsequently, manufacturing coordination *evaluates the scenarios* with support from the involved local site managements and the production network planners of the considered products.

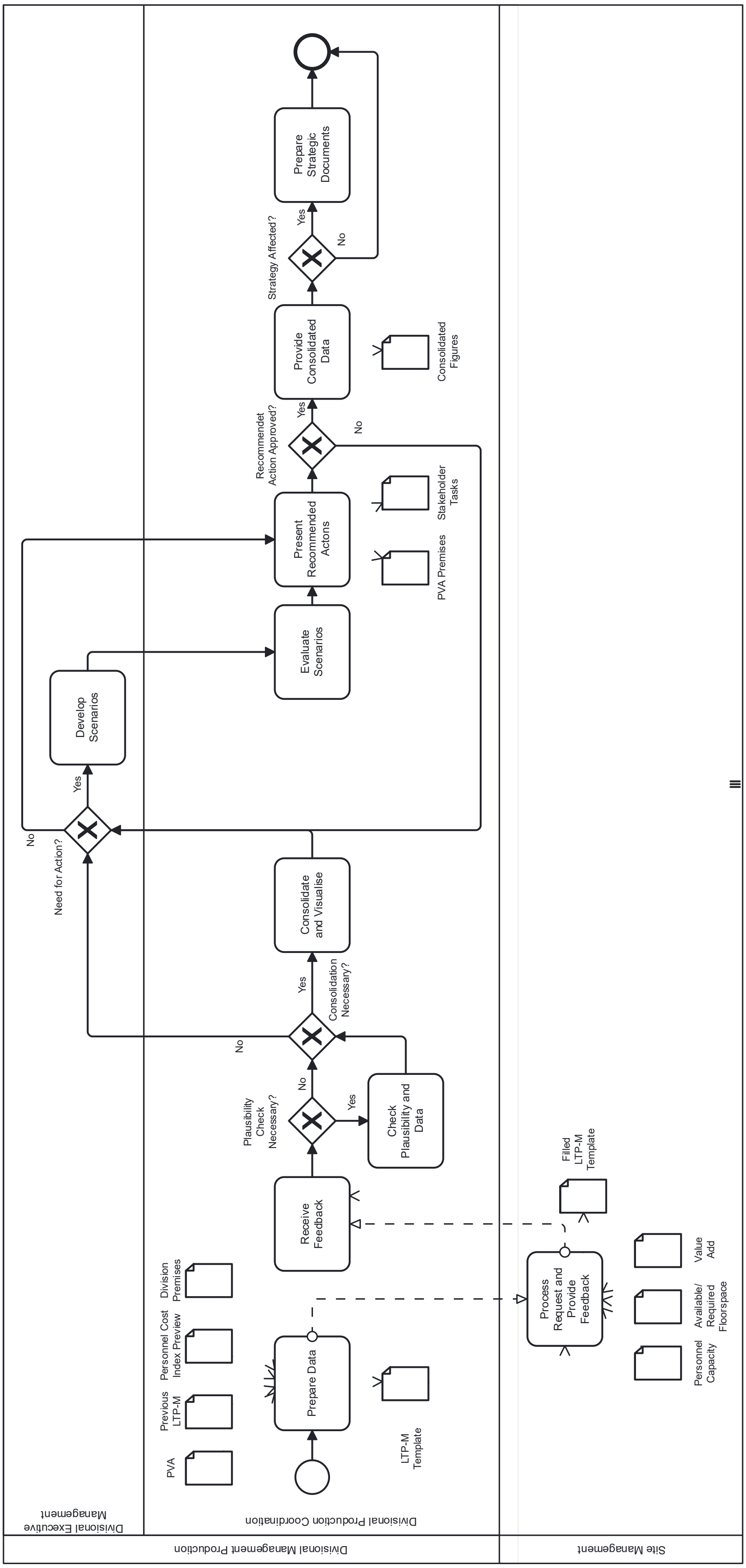

Figure A 19: Existing Long-Term Planning Manufacturing Process

Table A 23: Responsibility Assessment Matrix for LTP-M Process

Process	Divisional Executive Management	Divisional Production Coordination	Site Management	Central Technology Coordination
Prepare Data		Responsible		
Process Request and Provide Feedback		Support	Responsible	
Receive Feedback		Responsible		
Check Plausibility and Data		Responsible	Support	
Coordinate and Visualise	Informed	Responsible		
Develop Scenarios	Responsible	Support		
Evaluate Scenarios	Support	Responsible		Support
Present Recommended Actions	Approval	Responsible		
Provide Consolidated Data		Responsible		
Prepare Strategic Documents		Responsible		

Next, manufacturing coordination *presents of recommended actions*, which must be approved by the executive management. Based on those, the premises for the next PVA cycle and necessary tasks for stakeholders are determined and shared. Then, manufacturing coordination *provides consolidated data* of the results to the relevant stakeholders. If the decision is strategically important, they also *prepare* required *strategic documents*.

Within this process, a DSS could aid in assessing the necessary capacities of each IPN across the sites and to plan scenarios for capacity adaption, resource, and product variant allocation. As the APVA

In the following sections, the three phases of the structured design process for LTPA are described.

A7.1 Decision Type Analysis

The first phase establishes the time horizon, major system elements, and the desired AC. In the following sections, the most important steps of this process are described.

Determination of the Time Horizon

To determine the time horizon, the particular characteristics of the organisation and the decision variable with the longest time horizon need to be considered.

Organisational Characteristics

The relevant characteristics of the organisation are illustrated in Table A 24. In the following, only the important aspects are discussed. The size of the organisation is very large, implicating, a DSS even for strategic issues is used somewhat frequently. As the decisions are not made unilaterally by a central authority, but rather in a deliberative process between central authority and local sites, explainability needs to be high, but also, different interest and specifics need to be considered. The high production volumes and associated specialised equipment's for products are well suited to linear descriptions. The high tendency to split production volumes across sites makes the decision processes more complex, which is reflected in the organisational structure. The medium value density leads to logistic considerations playing a relevant role for the organisation.

Table A 24: Company Characteristics

Characteristic		Description	Value
FC01	Organisation Size	Size of the organisation in terms of turnover, employees, & sites.	high
FC02	Decision Centrality	Degree to which relevant decisions are centralised in the company	moderately high
FC03	Market Relation	Point of product creation process orders are introduced at	late
FC04	Resource Share	Share of resource costs in production costs	moderately low
FC05	Product Heterogeneity	Degree to which products of the organisation differ from each other	moderately high
FC06	Production Lead Time	Time between the start of production and finalisation of a product	low
FC07	Product Stability	Time a product type is sold in the market without change	moderately low
FC08	Vertical Integration	Share of value creation performed within the company	moderately high
FC09	Production Volume	Number of products produced	high
FC10	Production Technology Stability	Degree to which production technology remains stable across generations	moderately high
FC11	Commoditisation	Degree to which sales are determined by price	moderately high
FC12	Production Splits	Split of production across sites	high
FC13	Product Value Density	Value per volume or weight of product.	moderately high
FC14	Digital Maturity	Capabilities and IT infrastructure of the organisation	high

Identification of Lead Decision Variable

Next, the relevant decision variables and their time horizons need to be characterised. Table A 25 offers an overview of the considered decision variables and their role in the decision process. The time ranges are adapted to account for the specifics of the organisation.

Site set-up is outside the decision space. Site expansion and site consolidation can be considered but are not the focus of typical decisions. Technology set-up, move and consolidation can be part of the decision, but are not typical. Most sites have a set of existing technologies, predominantly automated assembly and changes in production technologies are rare. The primary focus of the decisions are production resource changes and personnel changes. As the production resources are relatively complex, set up times of one to two years can be expected. Personnel changes also concern countries with profound worker contract protection, so that especially large-scale workforce reductions may take up to three years or even more. Thus, personnel lay-offs can be considered the primary decision variable.

Table A 25: Relevant Decision Variables and Corresponding Time Horizons for LTPA

PNC Element	Change Mode	Role in Decision Process	Estimated Time range
Production Site	Set-Up	Fixed	3-4 Years
	Expand	(Optional) Subject	1-3 Years
	Consolidate	(Optional) Subject	2-3 Years
Auxiliary Site	Set-Up	Not considered	
	Consolidate	Not considered	
Logistic Site	Set-Up	Not considered	
	Consolidate	Not considered	
Supplier	Select	Not considered	
	Develop	Not considered	
Production Technology	Set-Up	(Optional) Subject	0.5-3 Years
	Move	Subject	0.5-2 Years
	Consolidate	Subject	6-12 Months
Production Resource	Set-Up	Subject	12-24 Months
	Move	Subject	3-12 Months
	Adapt	Subject	2-6 Months
	Consolidate	Subject	3-12 Months
Auxiliary Capability	Establish	Not considered	
	Consolidate	Not considered	
Personnel	Hire	Subject	1-24 Months
	Reteach	(Optional) Subject	1-12 Months
	Lay Off	Subject	0.5-3 Years
Tool	Create	Not considered	
	Move	Not considered	
	Discard	Not considered	
Transport Mode	Set-Up	Inconsequential	1-12 Months
	Cancel	Inconsequential	1-3 Months
Releases & Certifications	Acquire	Inconsequential	1-6 Months
Work Time Model	Change	Inconsequential	1-6 Months
Set-Up	Change	Not considered	

Determination of Time Horizon

Considering the change time necessary for the primary decision variable, a time horizon of at least six years, i.e. double the change time, is reasonable. A time horizon of eight years is mandatory in the existing process, which is reasonably close.

Selection of Major System Elements

The pursued objectives and the included domains are considered to select the major system elements for modelling.

Considered Objectives

As shown in Table A 26, several objectives are pursued in this decision type. In the table the selected objective variants are marked bold. For the decisions at hand, costs and utilisation are the primary objectives. The decisions do not consider the company success, as they focus on the operational side. While quality, delivery time, delivery reliability, and service levels are important for the organisation as a whole, they are not the subject of this decision. However, volume flexibility and robustness are noteworthy considerations. For the company, complexity and knowledge protection are not central in this decision. However, ESG objectives are considered in part as secondary objectives.

Table A 26: Considered Objectives for LTPA

Objective Category	Objective Type	Variants	Implications on DC 01	DC 02	DC 04	DC 08	DC 09	DC 10	DC 11
Operational Objectives	Costs	Static Total Costs, **Net Present Costs**, Equivalent Annual Costs, Unit Production Costs, Activity-Based Costing Evaluation, Risk-Adjusted Expected Costs, Emission Costs, Penalty Costs			-	-		++	
	Utilisation	**Capacity Utilisation Rate**, Overall Equipment Efficiency		-	--	--	++	++	-
Customer-related Objectives	Flexibility	**Volume Flexibility**, Sourcing Flexibility, Variant Flexibility, Delivery Flexibility	-	+	+		-	-	+
Dynamic & Structural Objectives	Dynamic Capabilities	Adaptability, Internal Flexibility, Value at Risk, **Robustness**, Recovery Time, Resilience Loss	--	+	++		-		++
ESG Objectives	Environmental Stewardship	**Global Warming Potential**, Water Consumption, Ecological Hazard, Biodiversity Effect, Captured Land		+	+	+	-	-	++
	Societal Responsibility	Worker Safety, **Job Security**, Living-Wage Coverage, Community Impact		+		+	-	-	++

Considered Domains

The existing process largely determines the domains considered. As illustrated in Table A 27, the considered domains are production, logistics, site and resource management, human resources management, and strategic management.

Table A 27: Domains Considered in LTPA

Domain		Description	Variants
Primary Domains	Production	Planning, control, and operation of value-adding transformation processes.	
	Logistics	Planning and coordinating logistic operations for sourced parts, inter-site transfers, and distribution.	
Support Domains	Site & Resource Management	Management and coordination of local infrastructure and assets.	
	Human Resource Management	Acquisition, management, and development of personnel.	strict worker protection laws/agreements
	Strategic Management	Strategic management and coordination, coordination of other domains	

Major System Elements

Based on the considered objectives and system elements, a selection can be made regarding the system elements to be included in the DSS. They include the decision variables listed in Table A 25 and other elements that result in decision variables. The result of this selection is shown in Table A 28.

Table A 28: Resulting Considered System Elements in LTPA

System Element	Description	Associated Decisions
Production Site	Sites with value-adding activities owned and operated by the focal company	Set-Up
		Expand
		Consolidate
Production Technology	Type of processing characterised by a specific set of necessary expertise and characteristics	Set-Up
		Move
		Consolidate
Production Resource	Machines, lines, and plants which are instantiations of a production technology.	Set-Up
		Move
		Adapt
		Consolidate
Personnel	Staff directly or indirectly associated with value creation, process expertise	Hire
		Reteach
		Lay Off
Transport Mode	Type of transport chosen on a specific route	Set-Up
		Cancel
Work Time Model	Policy by which worker capacity is determined temporarily	Change
Product Variants		Allocate

Deduction of Desired Analytical Capability

The last part of the first design phase consists of the consideration of external influences, the description of the DMC, and, finally, the determination of the desired AC.

External Influence Detailing

In the following the effect of relevant external influences is analysed. For this, a procedure inspired by the common Failure Mode and Effect Analysis is used. With this approach, the most concerning influences may be identified. In Table A 29 the likelihood and severity of changes and the likely effect on the decision are described and valued on a scale from 1 (very low) to 6 (very high). The predictability of those changes is also assessed from 1 (very high) to 6 (very low). An importance score is then calculated as the product of the three. The assessment is used both for the design of the DSS but also for the prioritisation of data acquisition.

Table A 29: Evaluation of External Influences for LTPA

Category	Dimension	Change		Effect		Predictability		Importance
		Description	**Score**	**Description**	**Score**	**Description**	**Score**	
Market & Market Development	Customer composition	Can change significantly following automotive sector developments and contractual negotiations.	3	May effect either order volumes or the viability of entire product families.	6	Difficult to predict development of customers	4	72
	Customer preferences	Changes according to normal cycles of the automotive market.	2	Primarily affects order volumes, but may also affect the viability of order volumes	5	Interests of customers are usually well known.	2	20
	Economically driven demand	Can change relatively quickly and significantly following developments of the economy at large.	4	Affects order volumes significantly.	4	Various predictors for economic development exist, though it remains difficult to estimate.	3	48
	Competition	As the considered products require high investments, changes are relatively slow.	2	Can affect order volumes and product family viability.	5	Changes in competition can be tracked relatively closely.	2	20
Cost Factors	Labour costs	Changes occur slowly.	2	Large changes can affect the profitability of local production.	3	Labour costs developments can be precited quite well.	2	12
	Capital costs	Changes occur mostly slowly, but with large differences.	3	Changes affect primarily investment costs and inventory costs.	3	Changes in capital costs, can be predicted reasonably well	3	27
	Material costs	Changes to local material prices occur both concerning supplier developments (relatively slow changes) and material (relatively quick changes)	4	Material cost changes can have significant effects on profitability.	3	Changes in material costs are in part difficult to predict, though large developments can be predicted.	3	36
	Energy costs	Changes to energy costs occur mostly slowly.	2	The effect of energy cost changes is relatively low, though specific processes can be affected.	2	Changes to energy costs can be predicted relatively well.	3	12
	Communication costs	Changes occur very slowly	1	The effect of communication cost changes is low.	1	As changes depend on technological advances, they are relatively predictable.	2	2
	Local productivity	Productivity is primarily shaped by the organisation's production equipment, though some changes can occur.	2	Changes affect the profitability of local production.	3	Changes in productivity can be predicted relatively well.	2	12
Logistics	Supply availability,	Changes can occur relatively quickly; however, most suppliers have long-term contractual agreements	3	Does not affect long-term decisions much	1	Changes occur relatively sudden, but aggregate risk prediction is possible.	3	9
	Transportation costs	Changes occur with moderate speed but can have significant cost effects	3	Changes can significantly impact the profitability of local production.	3	Developments are reasonably well predictable	3	27
	Inventory costs	Changes occur infrequently and with relatively small effects	2	Inventory costs can in some cases affect decisions.	2	Changes can be predicted relatively well.	2	8
	Transport lead time	Changes occur infrequently and with limited effects.	2	Effects are limited to increases in transportation and inventory costs.	1	Changes are very predictable.	1	2
People	Training levels	Changes occur slowly but alter the capability profile of employees.	2	Training level changes affect availability and training costs of new personnel	3	Changes are very predictable.	1	6

Category	Dimension	Change		Effect		Predictability		Importance
		Description	Score	Description	Score	Description	Score	
	Employee turnover rate	Changes occur relatively slowly but fundamentally alter the relation between employees and organisation.	2	Turnover affect the personnel planning of the organisation overall.	4	Changes in turnover rate are predictable	2	16
	Cultural preferences	Changes occur slowly. They can impact the organisational culture.	1	Changes in culture can affect personnel retention and productivity.	2	Changes are slow but challenging to detect.	3	6
Legal Factors	Rule of law	Changes appear relatively slowly. Lacking rule of law is a large problem for the organisation.	2	Changes can make operation in a country non-viable in the extreme.	4	Changes are relatively predictable outside specific emergencies	3	24
	Knowledge protection	Changes appear moderately slowly, and changes are significant for the organisation.	2	Changes can make the production of specific components unviable.	3	Changes are relatively predictable but not always easy to track.	3	18
	Corruption	Changes appear slowly but are critical for the organisation.	2	Changes can make operation in a country non-viable in the extreme.	4	Changes are relatively predictable.	2	16
Political & Governmental Factors	Political stability	Changes appear slowly but can become critical for the organisation.	2	Changes can make operation in a country non-viable in the extreme.	4	Changes are relatively predictable, outside of extreme events.	3	24
	Subsidies	Subsidies can be offered on moderately short notice, with significant economic effects.	4	Subsidies can make production in a country economically viable.	3	Changes are somewhat predictable.	3	36
	Currency	Currency fluctuations can appear suddenly and with large effects, particularly between different currency blocks, which the organisation serves.	4	Currency changes can drastically change the economic viability of local production.	4	Larger trends in currencies are relatively predictable, but a large volatility is difficult to predict.	3	48
	Duties	New duties may be the result of sudden political intervention and have large economic effects.	5	Changes in duties can significantly alter the economic viability of local production.	3	Changes in duties are difficult to predict precisely, though larger trends can be observed relatively well.	4	60

The analysis shows that particularly *market & market development* and politic*al & governmental factors* are relevant. In addition, some of the local *cost factors* and *logistical costs* are relevant. This analysis informs the subsequent DMC structuring, AC deduction and later DSS design.

Decision-Making Committee Structuring

The DMC for LTPA is based on the responsibilities assigned in the LTP-M process. Thus, the main user of the DSS and responsible person for decision preparation, evaluation and proposal are the divisional manufacturing coordinators. The approval and thereby ultimately decision-making is allocated with the divisional executive management, while the local site management, logistic planning, and network planners are supporting decision-making.

Desired AC Deduction

The last step of the first phase is the deduction of the desired AC of a model. For this purpose, the previously assessed influences on the decision situation are considered and each decision situation characteristic is evaluated on a scale from 1 (very low) to 6 (very high). Table A 30 provides an overview of the evaluation of the decision characteristics as well as an explanation for each chosen evaluation. Furthermore, it shows the resulting flow values for each characteristic and the resulting desired AC value of -0.02. This indicates a preference for partially prescriptive models, i.e. models that incorporate a significant prescriptive part in their set of subject decision variables. The next section examines the specification of this set, the corresponding method selection, and interactions with APVA in detail.

Table A 30: Assessment of Desired AC for LTPA

Decision Situation Characteristic		**Weight**	**Value**	**Flow**	**Description**
DC 01	System Linearity	0.08	4	0.02	Moderately high: Superposition of IPN is mostly linear but some non-linearities in area calculation exist.
DC 02	Number of Decision Variables	0.10	3	-0.02	Moderately low: Decisions mostly focus on investments, line consolidations, and personnel development, if allocation decisions are not considered in detail.
DC 03	System Expertise	0.02	4	0.00	Moderately high: Good overall information availability but lacking proximity to local production and high product heterogeneity.
DC 04	Uncertainty	0.06	5	-0.03	High: Affected by several influences. Increased due to superposition of IPN.
DC 05	Decision Frequency	0.10	4	0.02	Moderately high: Regular planning intervals and additional decisions, but limited frequency due to high abstraction level.
DC 06	Decision Routine	0.08	4	0.02	Moderately high: Well described decision process and goals, but regular deviations due to special considerations of different sites or IPNs.
DC 07	Development Capabilities	0.04	5	0.00	High: Good availability of developers.
DC 08	Perspective Diversity	0.03	5	-0.02	High: Several sites, IPNs, and functions are part of the decision process.
DC 09	Achievable Accuracy	0.06	4	0.01	Moderately high: The available data and accuracy of available models allows reasonable accuracy.
DC 10	Objective Quantifiability	0.10	4	0.02	Moderately high: Decision focuses mostly on utilisation and costs, but some site-specific aspects are difficult to quantify.
DC 11	Data Acquisition Intensity	0.06	2	0.03	Low: Most data required is readily available, especially when considering PVAs as a given input.
DC 12	Time Horizon	0.10	4	-0.02	Moderately high: Relatively long time horizon due to personnel changes and investments.
DC 13	Decision Time	0.10	3	0.02	Moderately low: Given process only allows for relatively short decision times of multiple weeks.
DC 14	Computing Capabilities	0.01	5	0.00	High: Good availability of computing capabilities.
DC 15	Desired Explainability	0.04	5	-0.02	High: Strategic decisions need to be explainable to both management and the broader personnel.
DC 16	Model Expertise	0.01	4	0.00	Moderately high: Model users are well educated and familiar with simple predictive and prescriptive models.
	Sum	**1**		**0.03**	

A7.2 Method Composition

The second phase first details procedural factors of the decision situation necessary for method selection. Then it considers the interactions between the to be developed LTPA tool and the existing APVA systematically using the methodology introduced in 4.2.4. Finally, the DSS method architecture is determined.

Procedural Factor Determination

Objective Particularisation

In the following, the objectives considered in LTPA are further detailed. The considered objectives are (i) costs, (ii) utilisation, (iii) flexibility, (iv) robustness, and (v) ESG objectives.

The *costs* of decisions need to be considered as comprehensively as possible. In this context costs are considered in terms of the entire system, piecewise costs are not considered. Relevant costs in this context arise from several sources:

- *Infrastructure costs*: Occur as investment costs in buildings and other infrastructure and maintenance costs. A precise attribution of these costs to specific production equipment is difficult and changes to the infrastructure and thus alteration of the costs are not the focus of LTPA. Thus, infrastructure related costs are not considered.
- *Equipment costs*: Occur as investments in new lines or upgrades. Whereas these costs are considered as depreciation in accounting contexts, for the decisions considered here one-time investments are a more apt representation[96]. These costs occur whenever new equipment is acquired. Include the costs of the equipment itself, as well as shipping and set-up.
- *Labour costs*: Occur for personnel working to produce the goods the organisation provides. Is separated into direct personnel costs and indirect personnel costs. Includes wages and all overhead costs and taxes associated with the personnel.
- *Operating expenses*: Costs associated with the continuous operation of equipment, including maintenance parts, energy, and utilities.
- *Logistics costs*: Costs of logistic processes into, within and out of the organisations production network. This includes the costs of transportation, transhipping, warehousing, duties, and logistic-related taxes.
- *Licence costs*: Cost of production licences for regulatory purposes and customer requirements.
- *Material costs*: Cost of goods and parts consumed in the production process.

[96] Particularly, as precise piecewise costs are not pursued.

Utilisation serves as a replacement for costs that are difficult to assess. In particular, this is true for infrastructure costs. Instead of minimising infrastructure costs, LTPA focuses on maximising space utilisation in the sense, that infrastructure investments due to space demand are avoided if possible and consolidations are made possible. Furthermore, utilisation of existing personnel is used.

Flexibility describes the degree to which reorganisation of production to accommodate changed requirements is possible. It may thus be categorised by the type of allowed change. For long-term planning, the primary desired flexibility is volume flexibility within products between production sites. This flexibility describes whether production volumes of one product can be shifted to another site without requiring additional equipment or licences, while neglecting the availability of free capacity. In LTPA, this flexibility is considered a boundary condition, which each IPN has to satisfy to a predetermined level.

Robustness captures the insensitivity of the solution to changes in the environment. As the analysis of external influences has established, the primary change of concern affects market demand. The robustness should thus capture the degree to which capacity match is immune against demand changes. It should also consider the severity of a mismatch, as a slight deviation, for example slightly to little overall area is most likely compensable by adapting layouts, whereas large deviations have more severe consequences. In LTPA the desired level of robustness can be determined by the users.

ESG objectives capture the adherence to environmental, societal, and governmental responsibility of the organisation. In this case the primary concerns are greenhouse gas emissions in terms of environmental protection and worker protections in terms of societal responsibility. The greenhouse gas emissions of the company that can be affected by LTPA primarily concern logistics and material sourcing. In LTPA, which decides on the capacity match, greenhouse gas emissions are not directly considered, but they find entry into the logistic and material cost calculations made to decide on area, personnel, and investment demand using the CO_2 price stipulated by the German Government. Worker protections are site dependent. For LTPA, contract related work regulations are of primary concern. They are considered in the limitations of retirements to voluntary early retirements and planned retirements, as well as a limitation of the leasing workforce.

External Influence Characterisation
In this step the external influences identified and rated in the first phase are characterised in detail and decisions on their representation in the decision process are made. The considered dimensions are (i) customer composition, (ii) economically driven demand, (iii) material costs, (iv) subsidies, (v) currency changes, and (vi) duties.

Customer composition and *economically driven demand* are primarily the concern of the sales function, which observes and forecasts them as part of the regular yearly planning process. Changes in volumes can occur multiple times per year and order. Order cancelations or new orders occur less frequently. In effect the forecasted demand per product changes about once a week. The changes For LTPA both dimensions lead to changes in the volume and occurrence of specific orders. For both dimensions, the relevant changes differ by product, as the customer base, both in terms of the individual customers and their regional distribution as well as disposition to economic changes differs by product. The number of possible developments is high, but substitution of demands is possible. Fluctuations are frequent. Thus, the customer composition and economically driven demand are considered as a noise factor with parameters provided by the sales department.

The organisation has long-term contracts with their suppliers, such that *material cost* changes are in large part not directly driven by fluctuations in market prices. Nevertheless, changes occur regularly. Material costs are considered in the yearly forecasts of the purchasing department. These are then included in the PVA and thereby indirectly included in LTP-M. For the initial implementation of LTPA an integration of material prices is not prioritised, as it would require integration with additional domains. However, in the future an integration both as a noise factor and with distinct decision scenarios is possible.

Currency changes occur frequently and affect both the cost of production in different countries and the sales margin. The latter effect is considered by the sales department in their forecast. The former can impact the variable production costs as well as material costs and investments. The fluctuation range depends on the considered regions. For developed countries fluctuations range around 15% per year, for developing countries the range may be larger. In the initial LTPA implementation currency fluctuations are not considered, due to the difficulty of assessing their precise effect in conjunction with organisational structure. A future integration as a noise factor is possible.

Subsidies and *duties* are politically driven factors that change relatively rarely but can have large effects. Precisely characterising both requires detailed regional and regulatory knowledge. Both are considered as part of strategic scenarios in LTP-M as far as they drastically alter the overall conditions.

Decision Variable Allocation

The next step is to capture the decision variable sets of LTPA and allocate them to prescriptive and predictive sets.

Figure A 20 provides an overview of the decision variable sets in LTPA, structured into decisions fixed before LTPA is used, decision subjects and inconsequential decisions. The latter two are further divided into the prescriptive and predictively determined sets. In the case of LTPA, there are no relevant inconsequential decisions.

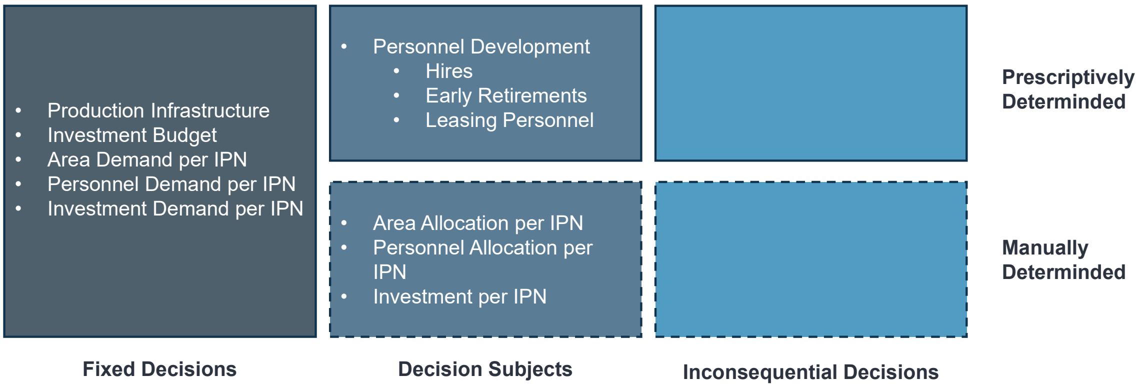

Figure A 20: Decision Variable Sets of LTPA

As discussed before, the relevant infrastructure including its area and shape available to produce is decided upon before the LTPA decision process. The same is true for investment budgets, although some alterations may be permitted. The capacity demands of IPNs are also considered a fixed input, in the form of area demand, personnel demand and investment demand.

LTPA decides on the personnel development pursued at each site through hires, early retirements, and the acquisition of leasing personnel. Furthermore, it allocates capacity to the different IPN in the form of area, personnel, and investment budget.

Personnel development can be captured well using a stochastic linear model. The relevant decisions on hiring quotas, early retirement offers, and leasing personnel can at least initially be made unilaterally, based on the personnel demand and expected developments. Even though the complexity is somewhat limited, optimality determining the trade-offs between the possible decisions is challenging. Thus, the personnel development is ideally prescriptively determined.

The allocation of site capacity to IPN is made in the context of several stakeholders and coincides with strategic decisions on site capabilities, technological developments, and others. Furthermore, decisions are subject to a large degree of uncertainty, for example with regard to actual area demand, construction times, and others. Finally, these decisions occur in the context of overarching objectives, which are difficult to quantify. Thus, the capacity allocation decisions are made manually with predictive decision support.

Decision Process Design

The next step represents a continuation of the decision-making committee structuring from phase 1. In this step, the desired AC and corresponding decision variable are taken into account and put into a temporal sequence. This also takes into account the existing LTP-M decision process and only alters it where necessary. Finally, other decision process characteristics like the formalisation, occasion termination type and occasion are also specified.

The LTPA DSS is designed to support the process steps from *receive feedback* to *provide consolidated data*. Throughout this process the responsibilities and sequence only changes marginally. Upon receiving the data from site management, the divisional production coordination now consolidates and visualises the capacity match for all sites. LTPA supports the identification of needs for action, so the involvement of the divisional executive management can be reduced, and corresponding scenarios can be generated ahead of time by the divisional production coordination. These different adaption options are then discussed with the executive management and a decision on the preferred action is made. Finally, the selected alternative is validated with the site management and network management before consolidated data is provided using LTPA.

The degree of formalisation using LTPA is slightly increased, as the capacity deviation types and corresponding consequences are specified. The process remains iterative, as final decisions are only made after agreement of the relevant stakeholders. In addition, LTPA could be used as part of a monitoring process, but this is only conceptualised as a subsequent option. The decision occasion remains part of a hierarchical schedule. However, LTPA is conceivably also usable in subjectively triggered or rule-based decision processes.

Multi-Model Design & Interaction with APVA

Relationship Analysis

Analysing the relationship between LTPA and APVA results in a semi-locked relationship. This relationship is not immediately obvious, as the specific decisions of LTPA and APVA do not exactly match. But APVA requires strategic premises of sites and available space for line investments, which are determined by LTPA in its capacity allocation concerning area, personnel, and investments. These LTPA decisions are predictively determined, i.e., $LTPA \rightarrow APVA$. LTPA uses information on the area, personnel, and investment demand of each IPN, which are part of the prescriptive subject set of APVA, i.e., $APVA \Rightarrow LTPA$. Thus, the resulting relation can be described as semi-locked: $APVA \rightharpoonup LTPA$. Since LTPA has this relation with several instances of APVA, a specific strategy to address the relationship is necessary.

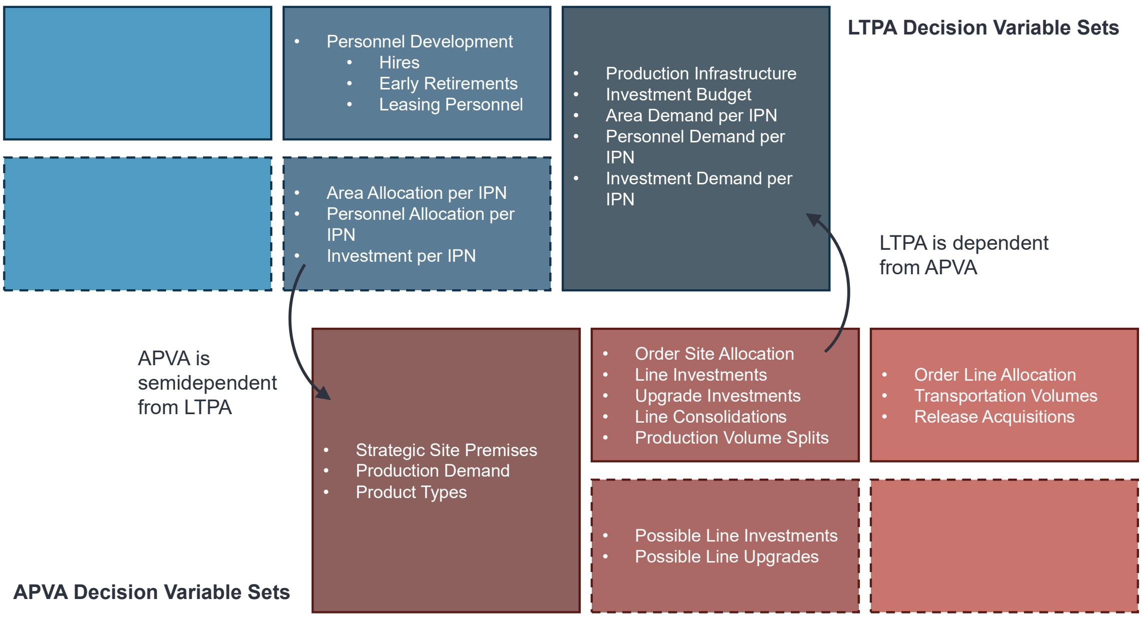

Figure A 21: Semi-locked Relationship Between LTPA and APVA

Resolution Strategies

In principle, several strategies are available to address locks. According to Table A 14, those are: (i) automatically iterate, (ii) manually iterate, (iii) combine, (iv) subsume, (v) predictively explore, and (vi) prescriptively explore. In the following, those options are discussed.

Automatic iteration would require a change of LTPA to convert the semi-locked to an interlocked relationship. However, this conflicts with the limited quantifiability of connected objectives and other reasons why the decision variables were put in the predictive set.

Manual iteration represents the previous way to address decisions in LTP-M. In this case capacity allocations that do not agree with the initial APVA results have to be returned to the APVA user to create a new plan. However, this process can be cumbersome and may not allow multiple possible options that include several IPNs to be considered. Thus, a faster, more integrated approach is preferable.

Combination would entail a full integration of APVA and LTPA into one model. Both models are principally compatible as the prescriptive methods of APVA could be applied in the prescriptive set of LTPA. However, the computing complexity and organisational complexity is prohibitive. This would require APVA models of several IPNs to be combined as well as the site-specific models, which would not be solvable in acceptable time. In addition, expertise from several different users is required making the organisational integration challenging.

In *subsumption*, the lower AC model, in this case LTPA is integrated into APVA. This would again necessitate a large number of APVA instances to be solved at once. Furthermore, the organisational integration would be even more difficult than it is in combination.

Predictive exploration describes the separation of the decision variable sets into the locked feasible decision set and the selection of solutions in this set for joint analysis of LTPA and APVA. In this case the allocation of capacity to IPNs can be used as the locked feasible decision set and the results of different solutions can be determined using multiple instances of APVA and LTPA. This requires relatively little additional implementation and limits the computational complexity. As the number of decision variables in this space is limited suitable solutions can be found manually. This also allows for the integration of non-quantitative objectives in the decision-making process.

Prescriptive exploration is similar to predictive exploration but uses suitable methods to prescriptively find the preferred solutions. It is computationally more complex but conceivable. It would however limit the use of non-quantitative objectives in these decisions.

Based on the assessment described above, predictive exploration is chosen as the strategy to address the semi-locked relationship. Prescriptive exploration could be implemented at a later stage. In the next step, suitable methods are chosen based on this strategy and the characteristics discussed in the previous section.

DSS Method Architecture

In the following methods for LTPA implementation are selected based on the previously defined characteristics. This includes the selection of the predictive methods, decision selection methods, configuration, and prescription methods, and finally scenario generation methods. If necessary, meta-modelling methods could also be included.

Predictive Method Selection
The first step is the selection of suitable predictive methods to determine the effects of personnel planning and capacity allocation on the chose objectives. The chosen objectives behave relatively linear vis-à-vis the considered systems. Furthermore, the time horizon and particularly period length is relatively long, making linear expressions more suitable. The desire for a partially prescriptive DSS makes a linear formulation attractive. However, the focus on robustness and the uncertainty in market development require a stochastic model. Thus, *stochastic mixed integer linear modelling* is chosen as the predictive method.

Using this method, the personnel development is modelled as the number of currently active full-time-equivalent (FTE) employees at each site and their change based on hiring and retirement rates. The development is modelled for different scenarios with decisions in the first periods fixed across the scenarios and recourse decisions beyond that. The demands are modelled using APVA and scaling factors for personnel, area, and investments.

Decision Selection Method Selection
The decision selection methods need to be selected for the different decision variables.

For the personnel planning the decision is made prescriptively. However, to uncover trade-offs between more conservative personnel planning and more aggressive personnel planning and adjustments in capacity allocation *post optimality analysis* can be used.

To select the preferred capacity allocations, which have to be made in conjunction with several different stakeholders, *negotiation techniques* can be applied.

Configuration Method Selection
The chosen predictive method for personnel planning allows for efficient solution using *mixed integer linear programming*. This solution is also the most computationally efficient and relatively easy to implement.

To configure different solutions in the locked decision space of APVA and LTPA, *design of experiments* can be used to allocate capacities to different IPNs. In most cases a partially factorial experiment plan provides sufficient insights.

Scenario Generation Methods Selection
Scenarios have to be designed for market-side developments and other factors.

Market-side developments are constituted of several distinct developments. Those developments can be substituting. In most cases, it is easier to estimate probabilities of specific events, than to predict coherent future developments with their overall probabilities. Thus *Monte-Carlo Simulation* with *receptor model* is chosen to generate scenarios. It is paired with a clustering technique to limit the number of scenarios in the stochastic model.

For other developments *scenario technique* is utilised to systematically identify relevant developments that need to be considered.

A7.3 Model Detailing

The third and last phase of DSS design takes into account the results of the previous phases to design the details of the resulting DSS with a focus on the predictive and prescriptive method. It consists of a first step, where the requirements and restrictions to consider are determined, and a second step, which specifies the DSS on this basis.

Requirements & Restrictions Determination

The requirements and restrictions are subdivided into five groups: (i) behavioural requirements, (ii) accuracy requirements, (iii) data restrictions, (iv) model restrictions, and (v) computational restrictions. For each category, specific boundary conditions are determined which limit the modelling freedom.

Behavioural Requirement Determination
The behavioural requirements (BR) contain all requirements that describe the dynamic behaviour of the model. The dynamic behaviour of the model should reflect the behaviour of the investigated system for the examined types of problems. The behaviours in question can concern common or rare states of the system and be limiting options or enforcing complexity. The requirements do not include assumptions that simplify the systems behaviour. The requirements are gathered by considering each modelled element of the system and their change modes. The resulting behavioural requirements are shown in Table A 31.

Table A 31: Behavioural Requirements Towards LTPA

Requirements		Description
BR01	Limited Hiring Rate	Hiring rates need to be constrained, as an integration of too many personnel at once is not possible.
BR02	Leasing Personnel Aversion	The employment of leasing personnel should be avoided where regular personnel can be employed without too much difficulty. The maximum quota of leasing personnel should be limited.
BR03	Rolling Horizon Personnel Planning	Personnel changes have to be committed for the upcoming year, so the same decisions have to be made irrespective of the considered scenario.
BR04	Area Remanence	Line constructions and consolidations require construction times, which have to be considered when allocating area to IPNs.
BR05	Indirect Personnel Scaling	Indirect personnel should scale with increasing order, resources, or direct personnel.
BR06	Overcapacity Preference	The personnel planning should prefer temporary overcapacity to temporary undercapacity.
BR07	Restrained Personnel Volatility	The personnel planning should accept some overcapacity to avoid aggressive hires and retirements to retain knowledge.

The relevant dynamic requirements concern the modelling of personnel, area remanence and the scaling of indirect personnel. In realistic scenarios, the hiring is limited to a quota of existing personnel as intensive training is usually necessary. The organisation has a strong social commitment, which results in several requirements. Leasing personnel allows for increased flexibility but should be limited and avoided if regular personnel can provide the necessary flexibility. The organisation prefers overcapacity to undercapacity of personnel to ensure orders can be fulfilled. Furthermore, personnel volatility should be avoided. It is assumed that indirect personnel demand changes based on factors such as order volumes, number of lines, or direct personnel. Finally, construction times for production areas need to be considered.

Accuracy Requirement Determination

The accuracy requirements (AR) include all specifications of model accuracy with respect to the predictive reflection of the real system. These requirements are determined based on an analysis of the objectives and the components contributing to them directly or indirectly. Depending on the type of value specified the requirements can be formulated differently. For continuous values, the requirements are stated as a range, within which a specified share of the results has to lie. For categorical assessments, the requirements are formulated as minimum α and β error rates. Table A 32 depicts the relevant accuracy requirements for LTPA.

Table A 32: Accuracy Requirements Towards LTPA

Requirements		Description
AR01	Costs of Personnel	The incurred costs of direct personnel should be within 10% of actual costs in 95% of cases.
AR02	Costs of Adaption	The costs of IPN adaption to limited capacity should be within 20% of the actual costs in 90% of cases.
AR03	Area Match	More than 95% of cases in which the actual area demand exceeds the available area should be detected. More than 80% of cases in which the actual area demand is satisfied should be detected as such.
AR04	Personnel Match	More than 90% of cases in which the actual personnel demand exceeds the available personnel by one FTE should be detected. More than 80% of cases in which the actual personnel demand is satisfied should be detected as such. More than 80% of cases, in which the actual available personnel exceed demand by more than one FTE should be detected. More than 75% of cases in which the available personnel are used should be detected.
AR05	Investment Costs	The investment costs should be within 20% of the actually necessary investment costs in 95% of cases.

The accuracy requirements concern primarily costs and the matching of areas and personnel. In terms of costs, the personnel costs have to be accurate to the actual personnel costs to meaningfully evaluate the trade-offs between adaptions and changed hiring strategies. The costs of IPN adaption to changed capacity should be relatively accurate. However, these costs only serve as an initial indication, thus moderate accuracy is sufficient. Not detected area exceedance could have severe consequences, as necessary adaptions would be delayed. Falsely detected area exceedance would lead to additional analysis, thus more moderate accuracy requirements are placed on this error rate. Personnel matching is less critical than area matching, as short-term adjustments are possible. For personnel undercapacity is more critical than overcapacity and falsely positive mismatches only lead to increased analysis. Finally, the investment costs should be relatively accurate to make sound decisions on them.

Data Restriction Determination

Several restrictions originate from the available data. These restrictions are uncovered by analysing available data sources for the data necessary for the model. These demands are initially based on an analysis of the included elements and their attributes. As a first step, these data demands are compared to the available data in the original LTP-M process. In many cases more detailed information may be available in the organisation, but not immediately accessible to the decision makers, either due to data privacy issues or organisational structure. Table A 33 aggregates the resulting restrictions towards the model.

Table A 33: Data Restrictions Towards LTPA

Restriction		Description
DR01	Personnel-Line Allocation	The attribution of personnel to specific lines is not consistently covered in data. In many cases only an attribution to IPNs is possible.
DR02	Personnel-Indirect Function Allocation	The attribution of indirect personnel to distinct indirect functions is not consistently available, only a connection to the site is possible.
DR03	Personnel Development	The anticipated development of personnel, especially in terms of planned retirements is only known in the aggregate. Changes in age composition due to early retirements are unknown.
DR04	Area-Line Attribution	The area covered by individual lines is not captured in data, instead area per production section, which may include multiple lines is available.
DR05	Line Size	The data does not describe how much of the area is fully covered by machines and what share are for example loading and buffer spaces.
DR06	Investment Cost Estimation	The necessary investment for new lines, upgrades, and changes are based on estimates of planners. The accuracy of those estimates is limited.

The data restrictions concern several aspects of LTPA. For the calculation of personnel data from the HR departments of the sites is used which includes the number of direct and indirect personnel per cost centre. This does not allow for line specific attribution of workers as multiple production lines are often collected under one cost centre. Furthermore, the possibility to attribute to distinct indirect functions is limited. The development of personnel is also only known in the aggregate, so total planned retirements of direct and indirect personnel. The attribution of area to the lines occupying it is only available based on production sections, which often include multiple lines. However, the area is specified as several distinct sections in different buildings and on different floors. Finally, the investment costs for lines and upgrades are only available as estimates based on the planners' knowledge, limiting cost accuracy.

Model Restriction Determination

Further restrictions originate from the chosen models. This primarily concerns limitations of behavioural representation, for example limited non-linear behaviour and enforced discretisation. It may also include more specific limitations of a model type if the model is already specified. In this case the modelling space is relatively open, but the use of APVA for network optimisation is predetermined. Table A 34 shows the relevant model restrictions (MR) for LTPA.

Table A 34: Model Restrictions Towards LTPA

Restriction		Description
MR01	Single Recourse Stage	The chosen model only allows for a binary distinction of recourse and non-recourse variables; a multi-period decisions process is not possible.
MR02	Discretised Periods	The periods in the model are discrete, changes can only occur between periods, not within them.
MR03	Only Full Time Equivalents	The personnel model only recognises full time equivalents; non-proportional effects of part time employees cannot be considered.
MR04	Linear Relation Between Direct and Indirect Personnel	The relation between direct and indirect personnel has to be linear.
MR05	One Dimensional Area	The area match can only be described in a one-dimensional match; geometric effects cannot be considered.

The specification of a linear model with fixed period lengths places some limitations on the personnel model such as linear relationships between direct and indirect employee demand and the assumption that personnel is represented fully by FTE. The discretised periods, limit changes to the ends of periods for all three types of demand. The area match is limited to a one-dimensional match, which is a major limitation, as geometrical aspects cannot be taken into consideration. However, this limitation is eased by the usually possible adaption of the geometric shape of production lines. Finally, the stochasticity is only considered in a single recourse stage, not a complex interplay between information acquisition and action.

Computational Restriction Determination

Computational restriction result from the available computing capabilities and their relation to the available decision time and problem complexity as well as the chosen solving methods. Limitations are identified through the consideration of complexity drivers. These drivers can for example be a particularly difficult to compute combination of decision variables. The single relevant computation restriction (CR) is shown in Table A 35.

Table A 35: Computational Restrictions Towards LTPA

Restriction		Description
CR01	Independent IPN Optimisation	Multiple IPN can only be optimised independently, as a combination of multiple APVA with dependencies would increase complexity to an extent that would make computation within a few days difficult.

In the considered case, the computational restrictions are relatively minor, as the envisioned personnel planning model

DSS Specification

In the following the requirements and restrictions specified in the previous section are used to determine abstraction levels, model expressions and delimitations.

Abstraction Level Selection

The suitable abstraction level can be crucial to limit data demands and ensure efficient computation. Based on the initial LTPA model several element types can be implemented at multiple abstraction levels. For effective model use it is crucial to determine the preferred abstraction levels based on the determined requirements and restrictions. Table A 36 shows the element types, the abstraction criteria that can be used and possible level for each of them. The chosen level is marked as bold[97].

Table A 36: Possible and Chosen Abstraction Levels for LTPA

Element	Abstraction Criterion	Abstraction Levels
Site	Strategic Business Unit	**Separated**, United
Area	Buildings	Separated, **United**
	Use	Specific Use, **Direct & Indirect**, United
Indirect Functions	Occupation	Specific Function, **Broad Function**, **United**
	IPN	Per IPN, **United**
Direct Personnel	IPN	Per IPN, **United**
	Production Line	Per Line, **United**
Investment Budget	IPN	Per IPN, **United**
Production Line	Processes	Per Step, **Per Process**
Periods	Timespan	**Continuous Choice**
IPN	Product	**Individual Product**, Product Family
	Value Stream Echelon	**Single Echelon**, United

In the following each decision is briefly discussed:

- Site: The organisation has several sites which are part of multiple strategic business units (SBUs). As the decision process is focussed on single SBUs those sites are considered separate.
- Area: Areas can be divided by building they belong to and the intended use, i.e., office space or production area. As lines should be able to shift between buildings, area is considered across buildings. However, direct and indirect areas are distinguished as indirect areas are usually not easily transformable to production areas.
- Indirect functions: Indirect functions can be distinguished by their occupation, i.e., the type of function like maintenance, process planning, intra-logistics, etc. and the IPN they are assigned to. To allow for different levels of available data and specificity both broad function distinction and complete unification across occupations are possible. Furthermore, it is assumed that indirect personnel can freely switch between IPN, thus they are considered united across them.

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[97] Where multiple levels are possible, depending on users' choice both are marked.

- Direct personnel: Can be differentiated by IPN and production line. For simplicity and due to limited data availability, both are considered as united, but a distinction into separate categories with possible retraining could be a worthwhile extension to increase precision.
- Investment budgets: Could be distinguished per IPN. As the budgets are allocated on a site basis, they are considered united.
- Production Line: Could be divided into separate process steps, i.e., stations or chunked by connected production processes. As a very fine granular distinction would not effectively increase decision options but complicate modelling, they are grouped by connected processes.
- Periods: Can in theory be chosen freely. For the chosen time horizon, a value and considering the shortest changes being personnel decisions half year periods are sensible. This also agrees with the established planning practice.
- IPN: Can be distinguished by single product or product family and single echelon or united across the entire value stream. Due to the decision granularity and differences in networks within product families and across value streams they are separated by product and single echelon.

Model Expression Selection

Choosing the correct expression for the systems behaviour in the model is crucial for achieving accuracy and limiting computational complexity of the model. Table A 37 portrays possible and selected choices for model expression, which are then discussed in the following.

Table A 37: Possible and Chosen Model Expressions in LTPA

Expression Choice	**Options**
Indirect Function Scaling	Nonlinear, **Linear Stepped, Fixed**
Indirect Function Scaling Base	Orders, Products, Lines, Area, **Direct Personnel**
Area Matching	Shape-based, **Unidimensional**
Deviation Norming	Manhattan-Norm, Euclidian-Norm, **Chosen Norm**
Deviation Weighing	Unweighted, **Scenario-Product,**
Age Model	**Fixed Quotas**, Adaptive

- Indirect Function Scaling: Describes how indirect function demand is scaled with its base factors. Can be completely nonlinear, a linear step function, or fixed values. To limit the complexity only linear stepped and fixed are allowed.
- Indirect Function Scaling Base: Describes by which base value the indirect functions scale. Options could be orders, products, lines, areas, and direct personnel.

As it is the most prevalent, direct personnel is chosen, but an extension to additional options could be made.

- Area Matching: Describes the comparison between area demand and offer. Could be shape-based or unidimensional. Due to lacking data and the high complexity of shape-based matching, unidimensional matching is chosen.
- Deviation Norming: Describes how deviation severity is normed across scenarios for deviations between demand and offer for area, personnel, and investments. Different relative norming schemes could be applied from a purely linear Manhattan norm to a quadratic Euclidean norm to a freely chosen norm. As the effect on the model complexity is high, a freely chosen norm is used, which can be tuned to correspond to actual severities based on observed scenarios.
- Deviation Weighing: Describes how deviations from different scenario combinations are weighed relative to each other. This could be unweighted or a product of the combined scenario occurrence probabilities. The latter is chosen to accurately reflect likelihoods.
- Age Model: The rate of retirements could be based on fixed assumed quotas or based on a comprehensive worker age model. In this case the former is chosen to limit complexity and as this information is readily available.

Delimitation Design

The task of delimitation design is to determine how the limits of the model should be designed. For this, the model elements are considered, and suitable elements are selected, as well as possible delimitation rules in model instantiation. In addition, dependencies between model elements that require replacement elements are uncovered. Table A 38 portrays possible element types that can be used as a delimitation criterion and the corresponding rules. Selected delimitation criteria and rules are marked as bold.

Table A 38: Possible and Selected Delimitation Sets for LTPA

Elements	Delimitation Rule
IPNs	**By Selected Set**, by SBU
Sites	**By Selected Set**, by SBU, by Region
Buildings	By Selected Set, by Type
Area Types	**By Selected Set**
Lines	By Selected Set, by Value Creation Step
Indirect Functions	**By Selected Set**
Periods	By Selected Set, by Available Data

In the following, the selection is described briefly:

- IPNs: Allows for a limited consideration of product families. To allow the highest specificity, they can be chosen by a selected set.
- Sites: Allows for a limited consideration of sites. To allow the highest specificity, they can be chosen by a selected set.
- Buildings: Allows for a consideration of specific buildings only. Not included due to higher resulting complexity.
- Area Types: Allows for non-directly value creating areas that are not easily convertible to be excluded from consideration. To allow for specificity of local conditions, they can be chosen by a selected set.
- Lines: Allows for a limited consideration of specific lines. Not chosen, as the combination of site and IPN filter yields suitable analysis sets.
- Indirect Functions: Allows for the exclusion of indirect functions that are not relevant to a decision or do not scale directly with production. Can be selected by set.
- Periods: Allows for a limited consideration of specific times. Not chosen due to limited benefits and apparent disadvantages when ignoring some periods.

Based on the above specified delimitation criteria, some model result may require information from element types outside of the modelled part of the system. Table A 39 shows the model results that require replacement elements and the corresponding elements.

Table A 39: Model Results and Corresponding Necessary Replacement Elements for LTPA

Model Results	Necessary Replacement Elements
Area Demand	Lines
Direct Personnel Demand	Lines
Investment Demand	Lines
Indirect Personnel Demand	Lines, Indirect Functions

Area, direct personnel, and investment demand and offer matching require a complete consideration of demand across a site. If only a sub selection of IPN is considered demands not originating from this set have to be represented. As the demands are summed across lines, a line replacement element per site is necessary that captures the cumulative demands across not considered IPNs.

Indirect personnel demand, scales with direct personnel and thereby also requires the lines replacement element. In addition, an indirect function replacement element is needed for all indirect functions excluded from consideration.

A7.4 Data Demands of LTPA

The data demand (DD) of LTPA are organised based on the model elements. For each element, the corresponding set and relevant properties require corresponding data. These demands do not include discretionary parameters, which users can determine based on their preferred model behaviour. For example, the relative preference for overcapacity compared to undercapacity is specified by the user. Table A 40 shows the data demands of LTPA. The requirements towards it are based on estimations of effects on model accuracy according to the requirements specified above.

Table A 40: Data Demands of LTPA

Model Element	Data Demand		Demand Type	Accuracy Requirements	Other Requirements
Site	DD01	Sites	set		Timeliness: fully updated Completeness: 100%
	DD02	(Planned) Site Area	numerical	95% accurate	Timeliness: < 2 months Completeness: 100%
	DD03	Direct Personnel	numerical	98% accurate	Timeliness: < 2 months
	DD04	Indirect Personnel	numerical	95% accurate	Timeliness: < 2 months
	DD05	Leasing Personnel	numerical	95% accurate	Timeliness: < 2 months
	DD06	Direct Personnel Planned Retirements per Period	numerical	95% accurate	Timeliness: < 2 months
	DD07	Indirect Personnel Planned Retirements	numerical	90% accurate	Timeliness: < 2 months
	DD08	Direct Personnel Costs	numerical	95% accurate	Timeliness: < 2 months
	DD09	Indirect Personnel Costs	numerical	90% accurate	Timeliness: < 2 months
	DD10	Leasing Personnel Premium	numerical	95% accurate	Timeliness: < 2 months
	DD11	Early Retirement Costs	numerical	95% accurate	Timeliness: < 2 months
	DD12	Training Costs	numerical	95% accurate	Timeliness: < 2 months
	DD13	Allowed Investments	numerical	95% accurate	Timeliness: < 2 months
IPN	DD14	IPNs	set		Timeliness: fully updated Completeness: 100%
	DD15	Adaption Costs per Scenario	numerical	90% accurate	
Scenario	DD16	Scenarios per IPN	set		Timeliness: fully updated Completeness: 100%
	DD17	Scenario Likelihood	numerical	100% accurate	Timeliness: fully updated Completeness: 100%
Line	DD18	(Planned) Lines	set	100% accurate	Timeliness: fully updated Completeness: 100%
	DD19	Line – Site Allocation	categorical	100% accurate	Timeliness: fully updated Completeness: 100%
	DD20	Line – IPN Relation	categorical	100% accurate	Timeliness: fully updated Completeness: 100%
	DD21	Line Base Area	numerical	95% accurate	Timeliness: < 2 months Completeness: 100%
	DD22	Planned Line Area per Scenario and Period	numerical	95% accurate	Timeliness: < 2 months Completeness: 95%
	DD23	Line Nominal Personnel Capacity	numerical	95% accurate	Timeliness: < 2 months Completeness: 100%
	DD24	Planned Line Personnel Demand per Scenario and Period	numerical	90% accurate	Timeliness: < 2 months Completeness: 95%

Model Element	Data Demand		Demand Type	Accuracy Requirements	Other Requirements
	DD25	Planned Line Investments per Scenario and Period	numerical	90% accurate	Timeliness: < 2 months Completeness: 95%
Indirect Function	DD26	Indirect Functions per Site	set	100% accurate	Timeliness: fully updated Completeness: 100%
	DD27	Indirect Function Scaling Type	categorical		Completeness: 100%
	DD28	Indirect Function Scaling Factor	numerical	90% accurate	Timeliness: < 2 months Completeness: 90%

A8 Long Term Planning Assistant

Table A 41: Symbols Used in Appendix A8

Symbol	Description	Unit
A	Set of orders	
A_k	Set of orders in IPN k	
α	Order	
B	Set of deviation solutions	
$\mathrm{B}_{t,s,\tau}$	Set of deviation solutions to address deviations in period t at site s of type τ	
β	Deviation solution	
$\delta_{\omega,t,s}^{(AREA)}$	Area shortage in scenario ω and period t at site s	m^2
$\delta_{\omega,t,s}^{(INV)}$	Exceeded budget in scenario ω and period t at site s	€
$\delta_{\omega,t,s}^{(NDV)}$	Personnel undercapacity in scenario ω and period t at site s	FTE
$\delta_{\omega,t,s}^{(NDV,DIR)}$	Direct personnel undercapacity in scenario ω and period t at site s	FTE
$\delta_{\omega,t,s}^{(NDV,IND)}$	Indirect personnel undercapacity in scenario ω and period t at site s	FTE
$\delta_{\omega,t,s}^{(PDV)}$	Personnel overcapacity in scenario ω and period t at site s	FTE
$\delta_{\omega,t,s}^{(PDV,DIR)}$	Direct personnel overcapacity in scenario ω and period t at site s	FTE
$\delta_{\omega,t,s}^{(PDV,IND)}$	Indirect personnel overcapacity in scenario ω and period t at site s	FTE
$\delta_{\omega,t,s}^{(PER)}$	Personnel deviation in scenario ω and period t at site s	FTE
$\delta_{t,k,s,\beta}^{(UPD)}$	Required change value to solve deviation in period t by IPN k at site s for solution β	
$\delta_{t,k,s,\beta,\phi}^{(UPD)}$	Required change value to solve deviation in period t by IPN k at site s for solution β of deviation type ϕ	
$\delta_{t,k,s,\beta}^{(UPD,AREA)}$	Required area change value to solve deviation in period t by IPN k at site s for solution β	m^2
$\delta_{t,k,s,\beta}^{(UPD,INV)}$	Required invest change value to solve deviation in period t by IPN k at site s for solution β	€
$\delta_{t,k,s,\beta}^{(UPD,NDV,DIR)}$	Required direct personnel demand decrease to solve deviation in period t by IPN k at site s for solution β	FTE
$\delta_{t,k,s,\beta}^{(UPD,NDV,IND)}$	Required indirect personnel demand decrease to solve deviation in period t by IPN k at site s for solution β	FTE
$\delta_{t,k,s,\beta}^{(UPD,PDV,DIR)}$	Required direct personnel demand increase to solve deviation in period t by IPN k at site s for solution β	FTE

Symbol	Description	Unit
$\delta_{t,k,s,\beta}^{(UPD,PDV,IND)}$	Required direct personnel demand increase to solve deviation in period t by IPN k at site s for solution β	FTE
$\tilde{\delta}_{\omega,t,s}$	Relative deviation in scenario ω and period t at site s	
$\tilde{\delta}_{\omega,t,s}^{(AREA)}$	Relative area shortage in scenario ω and period t at site s	
$\tilde{\delta}_{\omega,t,s}^{(INV)}$	Relative exceeded budget in scenario ω and period t at site s	
$\tilde{\delta}_{\omega,t,s}^{(PER)}$	Relative personnel deviation in scenario ω and period t at site s	
$\hat{\delta}$	Deviation threshold	
$v_{\omega,t,l}$	Ordered production volume at line l in scenario ω and period t adjusted for cycle times	PC
$\sigma_{t,s}$	Deviation criticality-index for period t at site s	
Φ	Set of deviation types	
ϕ	Deviation type	
$\phi^{(PDV,DIR)}$	Direct personnel overcapacity deviation	
$\phi^{(PDV,IND)}$	Indirect personnel overcapacity deviation	
Ω	Set of scenarios	
$\Omega_k^{(IPN)}$	Set of scenarios defined for IPN k	
$\Omega_\omega^{(SCS)}$	Set of IPN scenarios constituting site scenario ω	
$\Omega_s^{(SITE)}$	Set of scenarios defined for site s	
$\dot{\Omega}$	Original set of scenarios	
ω	Scenario	
$\dot{\omega}$	Original scenario	
$a_{\omega,t,l}^{(LINE)}$	Activity of line l in scenario ω and period t	
$a_{\omega,t,u}^{(UPG)}$	Activity of upgrade u in scenario ω and period t	
$b_{\omega,t,l}^{(LINE)}$	Building activity of line l in scenario ω and period t	
$b_{\omega,t,\alpha,l}^{(REL,LINE)}$	Release acquisition activity in scenario ω and period t for order α at line l	
$b_{\omega,t,\alpha,s}^{(REL,SITE)}$	Release acquisition activity in scenario ω and period t for order α at site s	
$b_{\omega,t,u}^{(UPG)}$	Building activity of upgrade u in scenario ω and period t	
$c_s^{(ERT)}$	Average costs of early retirements at site s	$\frac{€}{FTE}$

Symbol	Description	Unit
$c_s^{(LEA)}$	Differential costs of leasing employees compared to regular employees at site s	$\frac{€}{FTE}$
$c_l^{(LINE)}$	Building costs of line l	€
$c_s^{(NDV)}$	Costs of undercapacity at site s	$\frac{€}{FTE}$
$c_s^{(PDV)}$	Costs of overcapacity at site s	$\frac{€}{FTE}$
$c_{\alpha,l}^{(REL,LINE)}$	Release costs of order α at line l	€
$c_{\alpha,s}^{(REL,SITE)}$	Release costs of order α at site s	€
$c_s^{(TRN)}$	Training costs for new employees at site s	$\frac{€}{FTE}$
$c_u^{(UPG)}$	Upgrade costs of upgrade u	€
$d_{\omega,l}$	Capacity demand in scenario ω by line l	
$d_{\omega,t,k,s}$	Capacity demand in scenario ω and period t of IPN k at site s	
$d_{\omega,t,k,s,\phi}$	Capacity demand of type ϕ in scenario ω and period t of IPN k at site s	
$d_{\omega,t,s}$	Capacity demand in scenario ω and period t at site s	
$d^{(AREA)}$	Demand for area	m^2
$d_{\omega,t,k,s}^{(AREA)}$	Area demand in scenario ω and period t of IPN k at site s	m^2
$d_{\omega,t,s}^{(AREA)}$	Cumulated area demand in scenario ω and period t at site s	m^2
$d_{t,k,s,\beta}^{(MAX)}$	Constrained maximum demand by IPN k in period t at site s for solution β	
$d_{t,k,s,\beta}^{(MAX,AREA)}$	Constrained maximum area demand by IPN k in period t at site s for solution β	m^2
$d_{t,k,s,\beta}^{(MAX,INV)}$	Constrained maximum invest demand by IPN k in period t at site s for solution β	€
$d_{t,k,s,\beta}^{(MAX,NDV,DIR)}$	Constrained maximum direct personnel demand by IPN k in period t at site s for solution β	FTE
$d_{t,k,s,\beta}^{(MAX,NDV,IND)}$	Constrained maximum indirect personnel demand by IPN k in period t at site s for solution β	FTE
$d_{t,k,s,\beta}^{(MIN,PDV,DIR)}$	Constrained minimum direct personnel demand by IPN k in period t at site s for solution β	FTE
$d_{t,k,s,\beta}^{(MIN,PDV,IND)}$	Constrained minimum indirect personnel demand by IPN k in period t at site s for solution β	FTE
$d^{(PER)}$	Demand for personnel	FTE
$d_{\omega,t,k,s}^{(PER)}$	Demand for personnel in scenario ω and period t of IPN k at site s	FTE

Symbol	Description	Unit
$d_{\omega,t,s}^{(PER)}$	Demand for personnel in scenario ω and period t at site s	FTE
$d_{\omega,t,k,s}^{(PER,DIR)}$	Demand for direct personnel in scenario ω and period t of IPN k at site s	FTE
$d_{\omega,t,k,s}^{(PER,IND)}$	Demand for indirect personnel in scenario ω and period t of IPN k at site s	FTE
$d_{t,k,s}^{(PER,LIM)}$	Maximum personnel demand possible in period t of IPN k at site s	FTE
$d_{l}^{(PER,NOM)}$	Nominal demand for direct personnel at line l at full capacity	FTE
$d^{(INV)}$	Demand for investments	€
$d_{\omega,t,k,s}^{(INV)}$	Demand for investments in scenario ω and period t of IPN k at site s	€
$d_{\omega,t,s}^{(INV)}$	Cumulated demand for investments in scenario ω and period t at site s	€
$e_{0,s}$	Number of regular employees at site s at period $t=0$	FTE
$e_{\omega,t,s}$	Regular employees in scenario ω and period t at site s	FTE
$e_{\omega,t,s}^{(ERT)}$	Early retirements in scenario ω and period t at site s	FTE
$e_{\omega,t,s}^{(HIR)}$	Regular hires in scenario ω and period t at site s	FTE
$e_{0,s}^{(LEA)}$	Number of leasing employees at site s at period t=0	FTE
$e_{\omega,t,s}^{(LEA)}$	Leasing personnel in scenario ω and period t at site s	FTE
$e_{\omega,t,s}^{(LEA,HIR)}$	Leasing hires in scenario ω and period t at site s	FTE
$e_{\omega,t,s}^{(PER)}$	Available personnel in scenario ω and period t at site s	FTE
$e_{t,s}^{(RT)}$	Planned retirements in period t at site s	FTE
g	Severity emphasis value	
i	Interest rate	
K	Set of IPNs	
K_s	Set of IPNs that can operate at site s	
k	Product-specific production network (IPN)	
L	Set of lines or production resources	
$L_{k,s}$	Set of lines associated with IPN k at site s	
L_s	Set of lines at site s	
l	Line or other production resource	

Symbol	Description	Unit
$o_l^{(LINE)}$	Area occupied by line l	m^2
$o_u^{(UPG)}$	Area necessary for upgrade u	m^2
$q_{t,s}^{(AREA)}$	Available area in period t at site s	m^2
$q_{t,s}^{(INV)}$	Investment budget in period t at site s	€
$q_{\omega,t,l}^{(NOM)}$	Nominal production capacity of line l in scenario ω and period t	PC
$r_{k,s}^{(DIR,IND)}$	Required indirect personnel per direct personnel for IPN k at site s	$\frac{FTE}{FTE}$
$r_s^{(ERT)}$	Maximum early retirement rate at site s	FTE
$r_s^{(HIR)}$	Maximum hiring rate at site s	$\frac{FTE}{FTE}$
$r_s^{(LEA)}$	Maximum leasing rate	$\frac{FTE}{FTE}$
$r_{k,s}^{(PER,AREA)}$	Required area per person for IPN k at site s	$\frac{m^2}{FTE}$
S	Set of sites	
s	Site/Plant	
T	Set of Periods	
t	Period	
$t_s^{(AERL)}$	Average number of periods shortened by early retirement at site s	
$t^{(REC,EMP)}$	Employees recourse threshold period	
$t^{(REC,LEA)}$	Leasing employee's recourse threshold period	
U	Set of upgrades	
U_l	Set of upgrades available for line l	
w_ω	Weight of scenario ω	

The Long-Term Planning Assistant (LTPA) is the result of multiple master theses supervised by the author. Its purpose is to support manufacturing planning across multiple product specific production networks, so called International Production Networks (IPN). It focusses on site capacity planning in the dimensions area, personnel, and investments. Whereas Appendix A7 illustrates the development process, this section focuses on the resulting DSS itself. Appendix A8.1 discusses the handling of scenarios from multiple IPNs in detail, Appendix A8.2 offers a detailed view of the personnel planning model, and Appendix A8.4 presents the design of injected restrictions. Finally, Appendix A8.5 offers insights into the developed user interfaces.

A8.1 Scenario Processing & Capacity Demand Calculation

In the following, the calculation of capacity demands across different IPNs and corresponding scenarios is illustrated.

Scenario Processing & Weighing

The automatically generated scenarios in APVA and LTPA are mainly driven by market and market development. In APVA scenarios are generated from a MC simulation of change drivers and resulting order volume developments. These scenarios are condensed into weighed clusters, which are used for stochastic optimisation of each IPN $k \in \mathrm{K}$ as described extensively by Brützel et al. (2025). The result is a set of order allocation and capacity development scenarios $\omega \in \Omega_k^{(IPN)}$, which are weighed such that:

$$\sum_{\omega \in \Omega_k^{(IPN)}} w_\omega = 1$$ *Equation A 105*

In the absence of information to consolidate scenarios, independence between the scenarios of different IPN is assumed. Then the resulting set of scenarios Ω across all IPNs K is described as

$$\Omega = \prod_{k \in K} \Omega_k^{(IPN)}$$ *Equation A 106*

To limit complexity, only a limited set of scenarios intersecting at a site is considered for that site:

$$\Omega_s^{(SITE)} = \prod_{k \in K_s} \Omega_k^{(IPN)}$$ *Equation A 107*

, where K_s denotes the set of sites that intersect at a site, i.e. that either operate or consider operating production resources at the site. The weight w_{ω_1} of each site scenario $\omega_1 \in \Omega_s^{(SITE)}$ is then given as the product of the constituting IPN-scenarios $\omega_2 \in \Omega_{\omega_1}^{(SCS)}$:

$$w_{\omega_1} = \prod_{\omega_2 \in \Omega_{\omega_1}^{(SCS)}} w_{\omega_2} \mid \forall \omega_1 \in \Omega_s^{(SITE)}$$ *Equation A 108*

The assumption of scenario independence can lead to an underestimation of edge scenarios if the scenarios between different IPNs are dependent. This could be the case in a general economic downturn, where order volumes would likely drop across multiple IPNs. As a determination of scenario dependence across IPNs is not possible, instead resulting edge scenarios on the site level need to be considered with increased care. Figure A 22 illustrates, how scenarios from only two sites already lead to a possible underemphasis of edge scenarios.

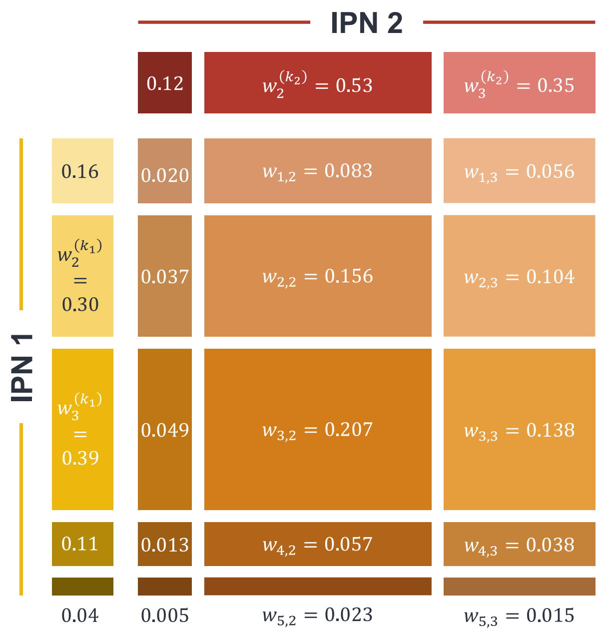

Figure A 22: Illustration of Scenario Products Across Two IPNs

Capacity Demand

The capacity demands are considered for space $d^{(AREA)}$, personnel $d^{(PER)}$and investments $d^{(INV)}$. For each category, the demand placed per network can be expressed. In each case the site-specific demand across the networks is determined as the sum of demands occurring across the constituting network scenarios

$$d_{\omega_1,t,s} = \sum_{\omega_2 \in \Omega_{\omega_1}^{(SCS)}, k \in K_s} d_{\omega_2,t,k,s} \qquad \textit{Equation A 109}$$

Area Demand

The area demand $d_{\omega,t,k,s}^{(AREA)}$ of an IPN k towards a site s in a scenario ω at period t may be expressed as

$$d_{\omega,t,k,s}^{(AREA)} = \sum_{l \in L_{k,s}} \left(o_l^{(LINE)} a_{\omega,t,l}^{(LINE)} + \sum_{u \in U_l} \left(o_u^{(UPG)} a_{\omega,t,u}^{(UPG)} \right) \right) + r_{k,s}^{(PER,AREA)} d_{\omega,t,k,s}^{(PER,IND)}$$

Equation A 110

where $l \in L_{k,s}$is the set of existing or potential lines of k at s, $o_l^{(LINE)}$ denote the area occupied by a line l, $a_{\omega,t,l}^{(LINE)}$ the lines activity, $u \in U_l$ the set of upgrades available for l, $o_u^{(UPG)}$ is the area addition necessary for the upgrade and $a_{\omega,t,u}^{(UPG)}$ the upgrade activity. $r_{k,s}^{(PER,AREA)}$ denotes the area demand per indirect employee and $d_{\omega,t,k,s}^{(PER,IND)}$ the demand for indirect employees as determined in the next section.

Direct Personnel

The direct personnel demand depends on the line utilisation assuming a linearity between utilised production capacity and required personnel capacity. The demand $d_{\omega,t,k,s}^{(PER,DIR)}$ is expressed as

$$d_{\omega,t,k,s}^{(PER,DIR)} = \sum_{l \in L_{k,s}} \left(d_l^{(PER,NOM)} \frac{v_{\omega,t,l}}{q_{\omega,t,l}^{(NOM)}} \right)$$

Equation A 111

where $d_l^{(PER,NOM)}$ is the nominal personnel demand of the line at full capacity, i.e. the total number of people necessary in a multi shift operation including planned vacation or sickness induced absences, $q_{\omega,t,l}^{(NOM)}$ is the nominal production capacity of the line accounting for its technical availability and cycle time, and $v_{\omega,t,l}$ is the volume of products produced adjusted for cycle times.

Indirect Personnel

The demand for indirect personnel $d_{\omega,t,k,s}^{(PER,IND)}$ is calculated using a fixed ratio to the direct employees $r_{k,s}^{(DIR,IND)}$:

$$d_{\omega,t,k,s}^{(PER,IND)} = r_{k,s}^{(DIR,IND)} d_{\omega,t,k,s}^{(PER,DIR)}$$

Equation A 112

Here only supporting indirect personnel associated with production, for example maintenance workers, are considered.

Investments

The demand for investments $d_{\omega,t,k,s}^{(INV)}$ is determined by expenditures for new lines, upgrades, and releases.

$$d_{\omega,t,k,s}^{(INV)} = \sum_{l \in L_{k,s}} \left(c_l^{(LINE)} b_{\omega,t,l}^{(LINE)} + \sum_{u \in U_l} \left(c_u^{(UPG)} b_{\omega,t,u}^{(UPG)} \right) + \sum_{\alpha \in \mathrm{A}_k} \left(c_{\alpha,l}^{(REL,LINE)} b_{\omega,t,\alpha,l}^{(REL,LINE)} \right) \right) + \sum_{\alpha \in \mathrm{A}_k} \left(c_{\alpha,s}^{(REL,SITE)} b_{\omega,t,\alpha,s}^{(REL,SITE)} \right)$$

Equation A 113

where $c_l^{(LINE)}$ denotes the costs of building a new line, $b_{\omega,t,l}^{(LINE)}$ the line building activity, $c_u^{(UPG)}$ describes the costs of upgrading a line with upgrade u, and $b_{\omega,t,u}^{(UPG)}$ is the upgrading activity. $\alpha \in \mathrm{A}_k$ is the set of all orders served in the network k, $c_{\alpha,l}^{(REL,LINE)}$ and $c_{\alpha,s}^{(REL,SITE)}$ are the costs of acquiring a release for line l and site s respectively, whereas $b_{\omega,t,\alpha,l}^{(REL,LINE)}$ and $b_{\omega,t,\alpha,s}^{(REL,SITE)}$ describe the release acquisition activity for l and s.

A8.2 Personnel Planning Model

Whereas the capacity planning models for investments and area are relatively simple and do not incorporate any prescriptive actions to amend capacity, the personnel planning is more complex. This model aims to determine capacity mismatches that arise even if the available flexibility is used. Those mismatches arise mainly if the rate of change in capacity demand exceed the elasticity of the personnel management. To determine the mismatches, the model determines hiring rates, early retirements, and the number of leasing personnel per period. For this purpose, a MILP model is formulated.

Objective Function

The model adheres to the following objective function:

$$\min \sum_{\omega \in \Omega_s^{(SITE)}} \left(w_\omega \sum_{t \in T} \left((1+i)^{-t} \left(c_s^{(NDV)} \delta_{\omega,t,s}^{(NDV)} + c_s^{(PDV)} \delta_{\omega,t,s}^{(PDV)} + c_s^{(TRN)} \left(e_{\omega,t,s}^{(HIR)} + e_{\omega,t,s}^{(LEA,HIR)} \right) + c_s^{(ERT)} e_{\omega,t,s}^{(ERT)} + c_s^{(LEA)} e_{\omega,t,s}^{(LEA)} \right) \right) \right) \mid \forall s \in S$$

Equation A 114

Where i is the nominal average interest rate, $c_s^{(NDV)}$ and $c_s^{(PDV)}$ are the punitive cost for undercapacity and overcapacity, $\delta_{\omega,t,s}^{(NDV)}$ and $\delta_{\omega,t,s}^{(PDV)}$ are the undercapacity and overcapacity at s in period t and scenario ω. $c_s^{(TRN)}$ denotes the training cost rate, $e_{\omega,t,s}^{(HIR)}$ the hires, and $e^{(LEA,HIR)}_{\omega,t,s}$ leasing hires. $c^{(ERT)}_{s}$ describes the early retirement cost rate, $e^{(ERT)}_{\omega,t,s}$ the early retirements, $c^{(LEA)}_{s}$ the leasing employee surcharge, and $e^{(LEA)}_{\omega,t,s}$ the number of leasing personnel.

Constraints

The model has to satisfy the following constraints:

Capacity Fulfilment
Deviations in capacity are captured in the under and overcapacity deviations.

$$e_{\omega,t,s} + e^{(LEA)}_{\omega,t,s} + \delta^{(NDV)}_{\omega,t,s} = d^{(PER)}_{\omega,t,s} + \delta^{(PDV)}_{\omega,t,s} \mid \forall \omega \in \Omega_s, t \in T, s \in S$$ *Equation A 115*

Hiring Rate
The rate of hiring $e^{(HIR)}_{\omega,t,s}$ is bounded by a rate $r^{(HIR)}_{s}$ of the absolute personnel count $e_{\omega,t-1,s}$, the assuming a site can only qualify a limited number of personnel at a time.

$$e^{(HIR)}_{\omega,t,s} \leq r^{(HIR)}_{s} e_{\omega,t-1,s} \mid \forall \omega \in \Omega_s, t \in T\backslash\{0\}, s \in S$$ *Equation A 116*

Employee Capacity Change
The change in capacity is determined by hires $e^{(HIR)}_{\omega,t,s}$, planned retirements $e^{(RT)}_{t,s}$, and early retirements $e^{(ERT)}_{\omega,t,s}$.

$$e_{\omega,t,s} - e_{\omega,t-1,s} = e^{(HIR)}_{\omega,t,s} - e^{(RT)}_{t,s} - e^{(ERT)}_{\omega,t,s} + e^{(ERT)}_{\omega,t-t^{(AERL)}_{s},s} \mid \forall \omega \in \Omega_s, t \in T\backslash\{0\}, s \in S$$ *Equation A 117*

where $t^{(AERL)}$_s describes the average early retirement length, i.e. the number of periods an employee retires before their planned retirement. For periods with $t < t^{(AERL)}_{s}$ $e^{(ERT)}_{t-t^{(AERL)}_{s},s}$ can be set as a parameter or directly integrated into $e^{(RT)}_{t,s}$.

Retirement Rate
The early retirements are limited to a maximum rate $r^{(ERT)}_{s}$ of the previous periods personnel number.

$$e^{(ERT)}_{\omega,t,s} \leq r^{(ERT)}_{s} e_{\omega,t-1,s} \mid \forall \omega \in \Omega_s, t \in T\backslash\{0\}, s \in S$$ *Equation A 118*

Leasing Rate
The maximum number of leasing personnel is limited to a site-specific rate $r_s^{(LEA)}$ of the permanently employed.

$$e_{\omega,t,s}^{(LEA)} \leq r_s^{(LEA)} e_{\omega,t,s} \mid \forall \omega \in \Omega_s, t \in T, s \in S$$
Equation A 119

Leasing Capacity Change
Increases in leasing are bounded by the leasing hires $e_{\omega,t,s}^{(LEA,HIR)}$.

$$e_{\omega,t,s}^{(LEA)} - e_{\omega,t-1,s}^{(LEA)} \leq e_{\omega,t,s}^{(LEA,HIR)} \mid \forall \omega \in \Omega_s, t \in T \backslash \{0\}, s \in S$$
Equation A 120

Non-recourse Employee Capacity
For the periods $t \in \{0, t^{(REC,EMP)}\}$, where $t^{(REC,EMP)}$ denotes the employee recourse threshold period, the employee capacity is fixed between scenarios.

$$e_{\omega_1,t,s} = e_{\omega_2,t,s} \mid \forall \omega_1, \omega_2 \in \Omega_s, \omega_1 \neq \omega_2, t \in \{0, t^{(REC,EMP)}\}$$
Equation A 121

Non-recourse Leasing Capacity
For the periods $t \in \{0, t^{(REC,LEA)}\}$, where $t^{(REC,LEA)}$ denotes the leasing recourse threshold period, the leasing capacity is fixed between scenarios.

$$e_{\omega_1,t,s}^{(LEA)} = e_{\omega_2,t,s}^{(LEA)} \mid \forall \omega_1, \omega_2 \in \Omega_s, \omega_1 \neq \omega_2, t \in \{0, t^{(REC,LEA)}\}$$
Equation A 122

Initiation
The starting capacities for regular personnel and leasing personnel is set as a parameter.

$$e_{\omega,0,s} = e_{0,s} \mid \forall \omega \in \Omega_s, s \in S$$
Equation A 123

where $e_{0,s}$ denotes the current number of employees.

$$e_{\omega,0,s}^{(LEA)} = e_{0,s}^{(LEA)}$$
Equation A 124

where $e_{0,s}^{(LEA)}$ denotes the current number of leasing employees.

Variable Definition
As a simplification, the variables are set to be continuous.

$$\delta_{\omega,t,s}^{(NDV)}, \delta_{\omega,t,s}^{(PDV)}, e_{\omega,t,s}, e_{\omega,t,s}^{(ERT)}, e_{\omega,t,s}^{(HIR)}, e_{\omega,t,s}^{(LEA)}, e_{\omega,t,s}^{(LEA,HIR)}, e_{t,s}^{(LEA,RT)} \in \mathbb{R}^{+} \mid \forall \omega \in \Omega_s, t \in T, s \in S$$

Equation A 125

Solution & Exemplary Results

The personnel planning model is solved using Gurobi as a commercial solver. The deviation penalty costs $c_s^{(NDV)}$ and $c_s^{(PDV)}$ can be consciously chosen to either encourage adaption on the APVA level when choosing low penalty costs and therefore higher deviations, or to adapt the personnel planning on site more heavily. Figure A 23 illustrates the personnel planning at a German site with demand for multiple different products. It shows the relative inflexibility of personnel development. The model allows for both positive and negative deviations to limit otherwise occurring early retirement costs. The illustrated capacity demand and offer is the mean of the considered scenarios.

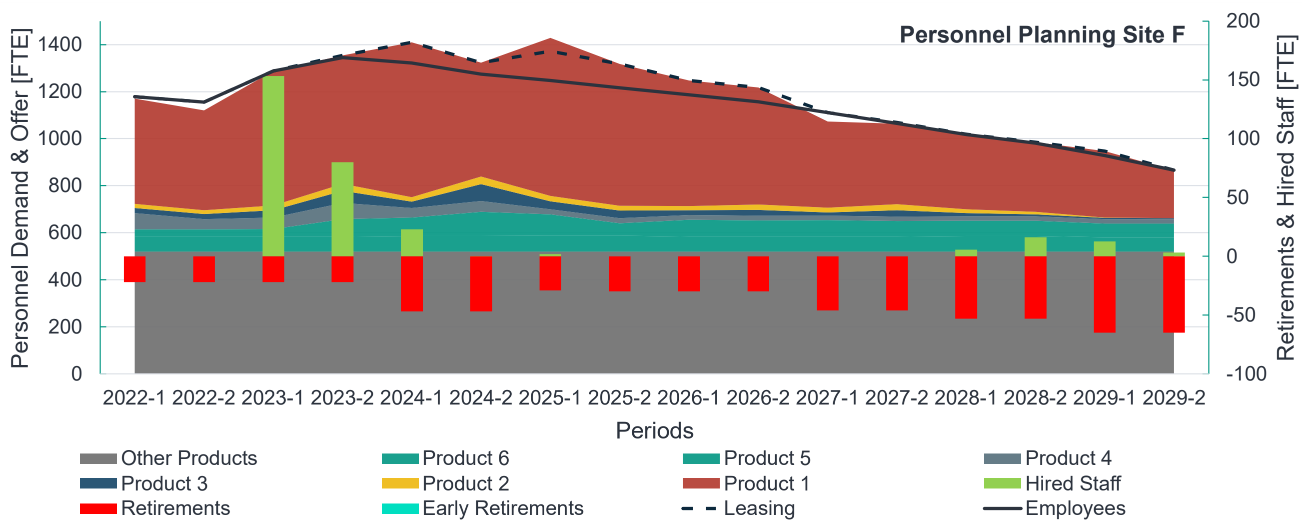

Figure A 23: Exemplary Personnel Planning Across Multiple IPNs

A8.3 Deviation Evaluation

In total, LTPA recognizes six types of deviations: area shortage $\delta_{\omega,t,s}^{(AREA)}$, exceeded budget $\delta_{\omega,t,s}^{(INV)}$, direct personnel shortage $\delta_{\omega,t,s}^{(NDV,DIR)}$, indirect personnel shortage $\delta_{\omega,t,s}^{(NDV,IND)}$, direct personnel surplus $\delta_{\omega,t,s}^{(PDV,DIR)}$, and indirect personnel surplus $\delta_{\omega,t,s}^{(PDV,IND)}$. Relative area shortages are expressed as:

$$\tilde{\delta}_{\omega,t,s}^{(AREA)} = \max\left(0, \frac{d_{\omega,t,s}^{(AREA)} - q_{t,s}^{(AREA)}}{q_{t,s}^{(AREA)}}\right)$$

Equation A 126

where $d_{\omega,t,s}^{(AREA)}$ is the cumulated area demand and $q_{t,s}^{(AREA)}$ the available area at t.

The relative exceeded budget is expressed as

$$\tilde{\delta}_{\omega,t,s}^{(INV)} = \max\left(\frac{0, d_{\omega,t,s}^{(INV)} - q_{t,s}^{(INV)}}{q_{t,s}^{(INV)}}\right)$$ *Equation A 127*

where $d_{\omega,t,s}^{(INV)}$ are the cumulated investments and $q_{t,s}^{(INV)}$ the available budget.

The personnel deviations $\delta_{\omega,t,s}^{(PER)}$ are determined using the above-described personnel model and put into proportion by the available capacity $e_{\omega,t,s}^{(PER)}$:

$$\tilde{\delta}_{\omega,t,s}^{(PER)} = \frac{\delta_{\omega,t,s}^{(PER)}}{e_{\omega,t,s}^{(PER)}}$$ *Equation A 128*

To assess the severity of deviations, a criticality-index $\sigma_{t,s}$ can be determined using:

$$\sigma_{t,s} = \sum_{\omega \in \Omega_s} \left(w_\omega \left(\frac{\tilde{\delta}_{\omega,t,s}}{\hat{\delta}} \right)^g \right)$$ *Equation A 129*

Where $\hat{\delta}$ denotes the deviation threshold and g describes the severity emphasis. Higher values of g lead to an increased impact of scenarios with large deviations.

$\hat{\delta}$ and g can be set for every deviation type. Choosing a suitable deviation threshold allows planners to change the sensitivity of different deviation types. Emphasising severe deviations is particularly important due to the independence assumption between scenarios discussed earlier. Severe deviations could for example occur if demand for most products declines simultaneously, driven by a single outside event. Under the assumption of independence, such scenarios would only cause a small change in the criticality index. This can be avoided by choosing higher values for g.

This severity-index allows for an easily accessible illustration of deviations as shown in Figure A 24. This allows planners to concentrate on the most critical deviations and develop suitable solutions as A8.4 discusses.

	2022-1	2022-2	2023-1	2023-2	2024-1	2024-2	2025-1	2025-2	2026-1	
Site A	A: 0.21 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.21 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.17 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.17 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.08 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.02 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	0.21
Site B	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.04 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.21 -IE: 0.00 +IE: 0.12	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.26 -IE: 0.00 +IE: 0.14	A: 0.09 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.09 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.09 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.09 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.09 FB: 0.00 -DE: 0.01 +DE: 0.00 -IE: 0.00 +IE: 0.00	0.28
Site C	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.01 -IE: 0.48 +IE: 0.00	A: 0.02 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.01 +IE: 0.00	A: 0.12 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.19 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.27 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.36 FB: 0.00 -DE: 0.01 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.30 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.30 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.30 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	0.48
Site D	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.50	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	0.50
Site E	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.03	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.01	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.06 -IE: 0.00 +IE: 0.08	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.05 -IE: 0.00 +IE: 0.07	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.17 -IE: 0.00 +IE: 0.18	0.18
Site F	A: 0.15 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.15 FB: 0.00 -DE: 0.00 +DE: 0.02 -IE: 0.00 +IE: 0.00	A: 0.15 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.15 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.01 +IE: 0.00	A: 0.15 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.01 +IE: 0.00	A: 0.15 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.02 +IE: 0.00	A: 0.15 FB: 0.00 -DE: 0.03 +DE: 0.00 -IE: 0.05 +IE: 0.00	A: 0.08 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.01 +IE: 0.00	A: 0.06 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	0.26
Site G	A: 0.02 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.03	A: 0.02 FB: 0.00 -DE: 0.00 +DE: 0.01 -IE: 0.00 +IE: 0.04	A: 0.02 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.01	A: 0.02 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.02 FB: 0.00 -DE: 0.00 +DE: 0.04 -IE: 0.00 +IE: 0.03	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.01 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.01 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.04 -IE: 0.00 +IE: 0.00	0.43
Site H	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.07 -IE: 0.00 +IE: 0.14	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.06 -IE: 0.00 +IE: 0.11	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.05 -IE: 0.00 +IE: 0.09	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.03 -IE: 0.00 +IE: 0.07	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.02 -IE: 0.00 +IE: 0.04	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.01 -IE: 0.00 +IE: 0.02	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.01 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	A: 0.00 FB: 0.00 -DE: 0.00 +DE: 0.00 -IE: 0.00 +IE: 0.00	0.14
	0.48	0.62	0.21	0.26	0.27	0.50	0.30	0.30	0.30	

Categories:	A: Area	FB: Financial Budget	-DE: Understaffing (direct)	+DE: Overstaffing (direct)	-IE: Understaffing (indirect)	+IE: Understaffing (indirect)				
Criticality:	low	≤ 0.1	medium	≤ 0.3	high	≤ 0.8	very high	≤ 2	extreme	> 2

Figure A 24: Excerpt of Deviation Overview for Multiple Sites, Deviation Types, and Periods

A8.4 Constraint Design

For each deviation instance with significant criticality a solution needs to be determined. A deviation instance is characterised by type ϕ, period t and site s. Solutions β can include contributions from all IPNs k that can contribute to the relevant demand. To generate solutions, the existing APVA models can be retried with additional constraints that ensure deviations are avoided throughout all scenarios. For a permissible solution, the demand quantity of all considered networks has to be changed by a change value $\delta_{t,k,s,\beta}^{(UPD)}$ which sum up to the maximum overall deviation:

$$\sum_{k \in K_s} \left(\delta_{t,k,s,\beta}^{(UPD)}\right) = \max_{\omega \in \Omega_s^{(\mathrm{SITE})}} \left(\delta_{\omega,t,s}\right) \mid \forall \beta \in \mathrm{B}_{t,s,\tau} \qquad \textit{Equation A 130}$$

Additionally, each change value may not exceed the permissible change of the demand. For solutions that require a reduction in use this results in the following:

$$\delta_{t,k,s,\beta,\phi}^{(UPD)} \leq \max_{\omega \in \Omega_k^{(\mathrm{IPN})}} \left(d_{\omega,t,k,s,\phi}\right) \mid \forall \phi \in \Phi \backslash \{\phi^{(PDV,DIR)}, \phi^{(PDV,IND)}\} \qquad \textit{Equation A 131}$$

For personnel overcapacity deviations, the change value $\delta_{t,k,s,\beta,\phi}^{(UPD)}$ results in the following

$$\delta_{t,k,s,\beta,\phi}^{(UPD)} \geq \max_{\omega \in \Omega_k^{(\mathrm{IPN})}} \left(d_{t,k,s}^{(PER,LIM)} - d_{\omega,t,k,s}^{(PER)}\right) \mid \forall \phi \in \{\phi^{(PDV,DIR)}, \phi^{(PDV,IND)}\} \qquad \textit{Equation A 132}$$

where $d_{t,k,s}^{(PER,LIM)}$ denotes the maximum capacity demand possible.

Figure A 25 shows a simple example of the relationships between capacity at a site $q_{t,s}$, the capacity demand $d_{\omega,l}$ resulting from multiple production lines $l \in L_s$ across several scenarios $\omega \in \Omega_s^{(\mathrm{SITE})}$. It also shows the resulting deviations and the constrained network demand at the site $d_{t,k,s,\beta}^{(MAX)}$.

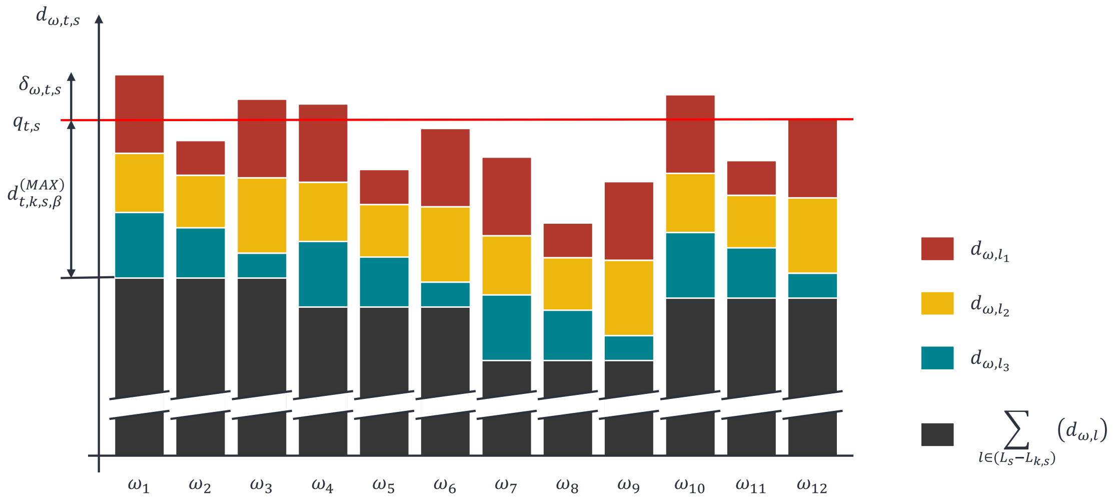

Figure A 25: Relationship Between Capacity and Demand Across Multiple Scenarios

Using the change values introduced earlier, additional constraints can be injected into APVA. For area deviations these are:

$$\sum_{l\in L_{k,s}}\left(o_l^{(LINE)}a_{\omega,t,l}^{(LINE)}+\sum_{u\in U_l}\left(o_u^{(UPG)}a_{\omega,t,u}^{(UPG)}\right)\right)+r_{k,s}^{(PER,AREA)}d_{\omega,t,k,s}^{(PER,IND)} \leq \max_{\dot\omega\in\dot\Omega_k}\left(d_{\dot\omega,t,k,s}^{(AREA)}\right)-\delta_{t,k,s,\beta}^{(UPD,AREA)} \coloneqq d_{t,k,s,\beta}^{(MAX,AREA)} \mid \forall\omega \in \Omega_k^{(\mathrm{IPN})} \qquad \text{Equation A 133}$$

where $\dot\omega \in \dot\Omega_k^{(IPN)}$ denotes the original set of scenarios used previously. For budget deviations the restriction is defined as:

$$\sum_{l\in L_{k,s}}\left(c_l^{(LINE)}b_{\omega,t,l}^{(LINE)}+\sum_{u\in U_l}\left(c_u^{(UPG)}b_{\omega,t,u}^{(UPG)}\right)+\sum_{\alpha\in\mathrm{A}_k}\left(c_{\alpha,l}^{(REL,LINE)}b_{\omega,t,\alpha,l}^{(REL,LINE)}\right)\right)+\sum_{\alpha\in\mathrm{A}_k}\left(c_{\alpha,s}^{(REL,SITE)}b_{\omega,t,\alpha,s}^{(REL,SITE)}\right) \leq \max_{\dot\omega\in\dot\Omega_k}\left(d_{\dot\omega,t,k,s}^{(INV)}\right)-\delta_{t,k,s,\beta}^{(UPD,INV)} \coloneqq d_{t,k,s,\beta}^{(MAX,INV)} \mid \forall\omega \in \Omega_k^{(\mathrm{IPN})} \qquad \text{Equation A 134}$$

For direct personnel undercapacity the constrained is formulated as follows:

$$\sum_{l\in L_{k,s}}\left(d_l^{(PER,NOM)}\frac{v_{\omega,t,l}}{q_{\omega,t,l}^{(NOM)}}\right) \leq \max_{\dot\omega\in\dot\Omega_k}\left(d_{\dot\omega,t,k,s}^{(NDV,DIR)}\right)-\delta_{t,k,s,\beta}^{(UPD,NDV,DIR)} \coloneqq d_{t,k,s,\beta}^{(MAX,NDV,DIR)} \mid \forall\omega \in \Omega_k^{(\mathrm{IPN})} \qquad \text{Equation A 135}$$

For indirect personnel undercapacity a similar constraint results:

$$r_{k,s}^{(DIR,IND)} \sum_{l \in L_{k,s}} \left(d_l^{(PER,NOM)} \frac{v_{\omega,t,l}}{q_{\omega,t,l}^{(NOM)}} \right) \leq \max_{\dot{\omega} \in \dot{\Omega}_k} \left(d_{\dot{\omega},t,k,s}^{(NDV,IND)} \right) - \delta_{t,k,s,\beta}^{(UPD,NDV,IND)} \coloneqq d_{t,k,s,\beta}^{(MAX,NDV,IND)} \mid \forall \omega \in \Omega_k^{(\mathrm{IPN})}$$

Equation A 136

For overcapacity, the formulas are slightly different. For direct personnel, the following results:

$$\sum_{l \in L_{k,s}} \left(d_l^{(PER,NOM)} \frac{v_{\omega,t,l}}{q_{\omega,t,l}^{(NOM)}} \right) \geq \min_{\dot{\omega} \in \dot{\Omega}_k} \left(d_{\dot{\omega},t,k,s}^{(PDV,DIR)} \right) + \delta_{t,k,s,\beta}^{(UPD,PDV,DIR)} \coloneqq d_{t,k,s,\beta}^{(MIN,PDV,DIR)} \mid \forall \omega \in \Omega_k^{(\mathrm{IPN})}$$

Equation A 137

Indirect personnel results in a similar formula:

$$r_{k,s}^{(DIR,IND)} \sum_{l \in L_{k,s}} \left(d_l^{(PER,NOM)} \frac{v_{\omega,t,l}}{q_{\omega,t,l}^{(NOM)}} \right) \geq \min_{\dot{\omega} \in \dot{\Omega}^{(IPN)}{}_k} \left(d_{\dot{\omega},t,k,s}^{(PDV,IND)} \right) + \delta_{t,k,s,\beta}^{(UPD,PDV,IND)} \coloneqq d_{t,k,s,\beta}^{(MIN,PDV,IND)} \mid \forall \omega \in \Omega_k^{(\mathrm{IPN})}$$

Equation A 138

Using these constraints, new APVA runs can be executed, to determine which solution β results in the lowest additional costs. For practical reasons, the constraints are typically placed on multiple periods, so that for example investments are not just shifted into the next period resulting in another deviation. Furthermore, multiple types of restrictions can be combined.

Figure A 26 shows an exemplary comparison of two adaption solutions, which relieve a deviation through changes in one network each. The figure shows that the adoption costs associated with product 3 are considerably higher, whereas the network for product 2 can adapt with much lower incurred costs. In particular, the variable costs increase significantly for product 3, as production has to be shifted to another site. This lets planners quickly assess different solutions. After the initial evaluation, the favoured solutions can be investigated in more detail to further increase confidence.

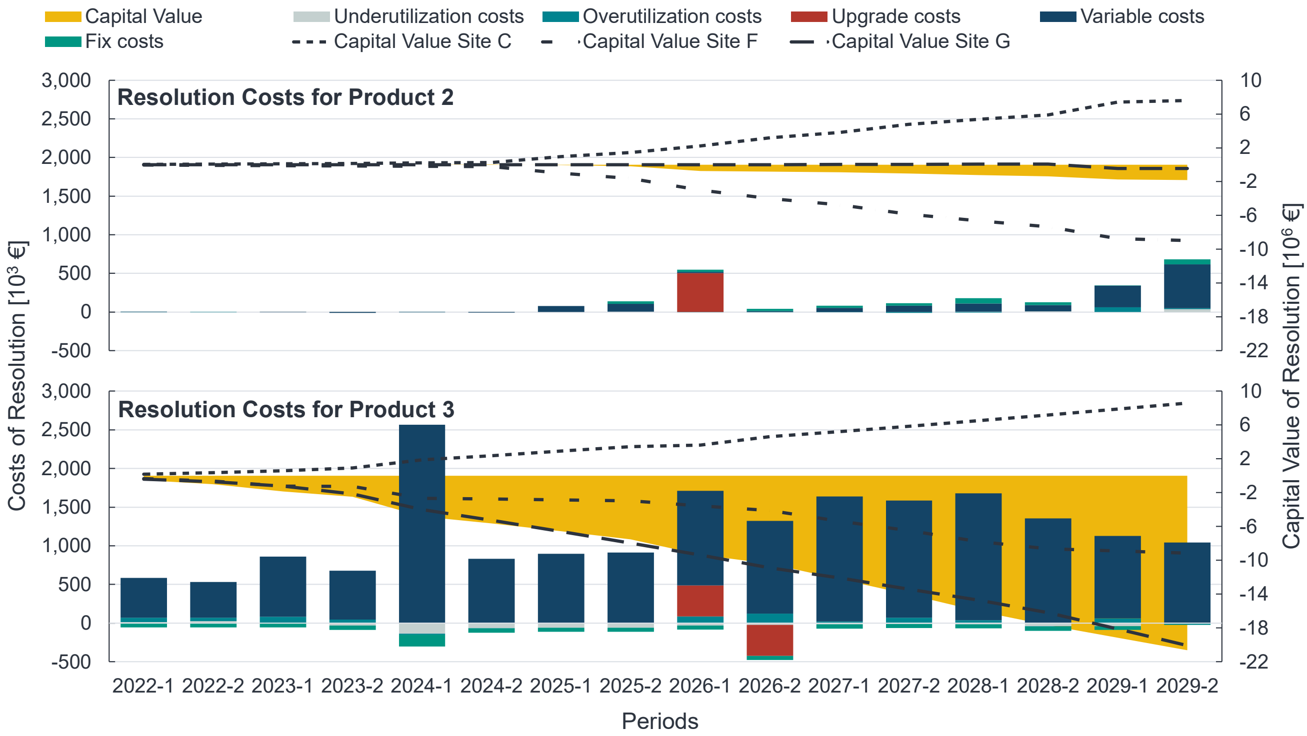

Figure A 26: Comparison of Average Costs of Adaption Options for a Capacity Constraint.

A8.5 User Interface

To support efficient decision-making, a user interface for LTPA is designed using Power BI as part of the master's thesis A_Bolender (2024) supervised by the author. In the following, the developed interfaces are briefly introduced[98].

Deviation Criticality Overview

An overview of deviations across types, sites, and periods is provided with the option to adapt each type's relative thresholds. For a better overview, the existing deviations are displayed on one table, and a detailed criticality index is given in another, as shown in Figure A 27.

[98] Any data that would allow inferences on protected information of the company is blurred.

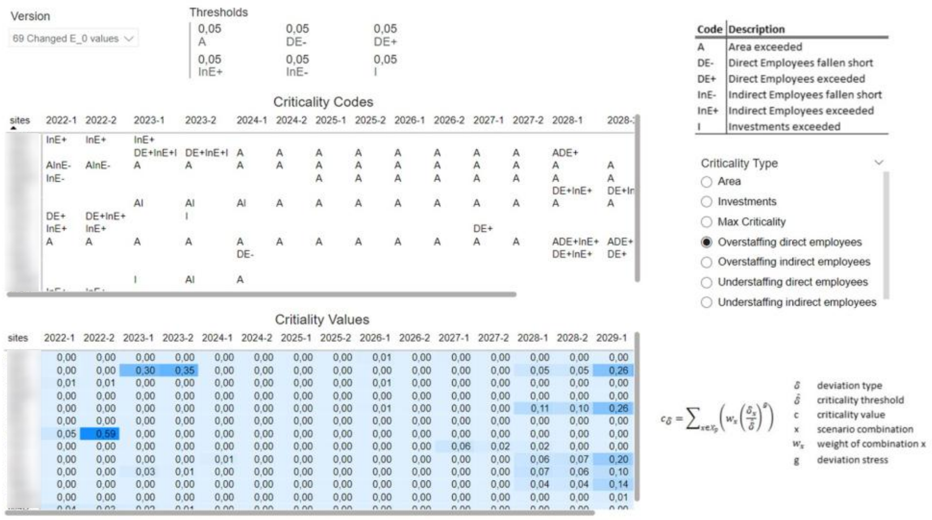

Figure A 27: LTPA Deviation Criticality Overview

Site Utilisation Overview

A crucial aspect of capacity demand and offer assessment are the utilisation of local lines. Figure A 28 shows a site utilisation overview indicating the utilisation of all lines of a selected site throughout periods. To contextualise the information, the range of utilisations across the scenarios $\omega \in \Omega_{k,s}^{(\mathrm{COM})}$ associated with a line $l \in L_{k,s}$ are illustrated, as well as the mean utilisation. Users can toggle different sites and lines of interest.

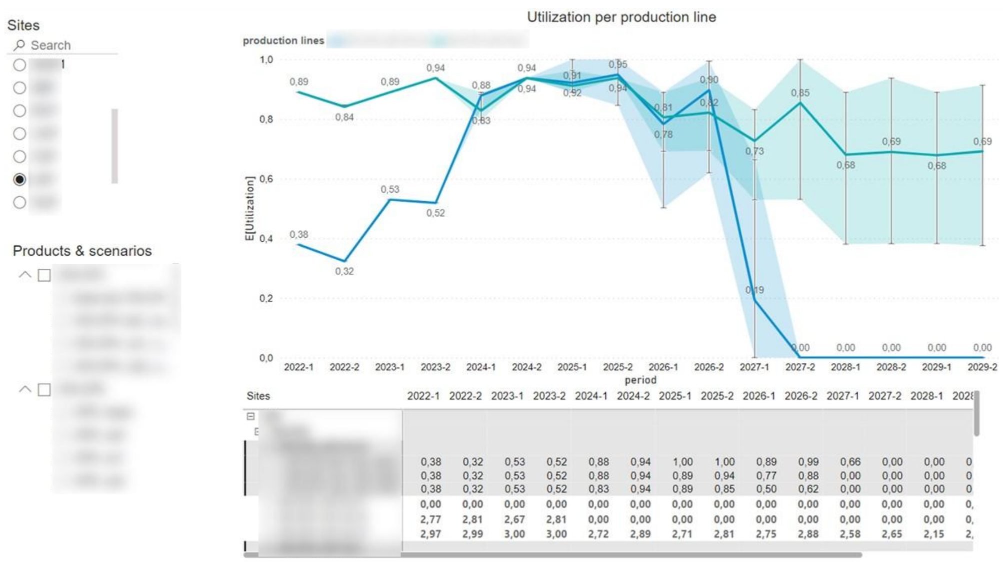

Figure A 28: LTPA Site Utilisation Overview

Investment Overview

Figure A 29 shows the investment overview by responsible network for a selected site with regard to the overall periodic site budget.

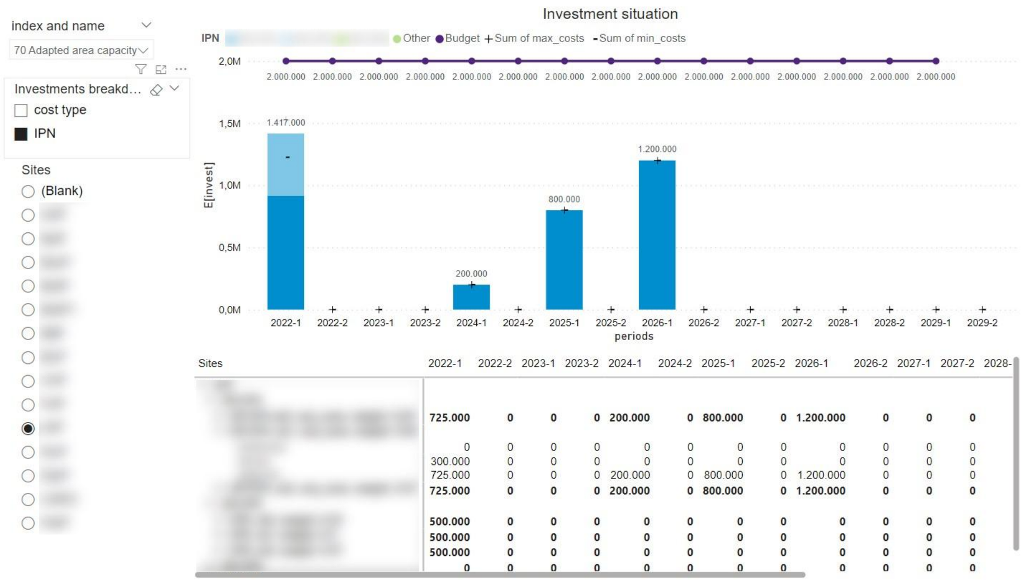

Figure A 29: LTPA Investment Overview

Personnel Planning Overview

To allow detailed planning of personnel capacity the corresponding dashboard shows the planned mean personnel capacity demand and offer across periods, split into regular and leasing employees, and contextualised with maximum and minimum demand values. The dashboard shown in Figure A 30 also provides a partitioning of the demands according to responsible networks and a detailed employee turnover view.

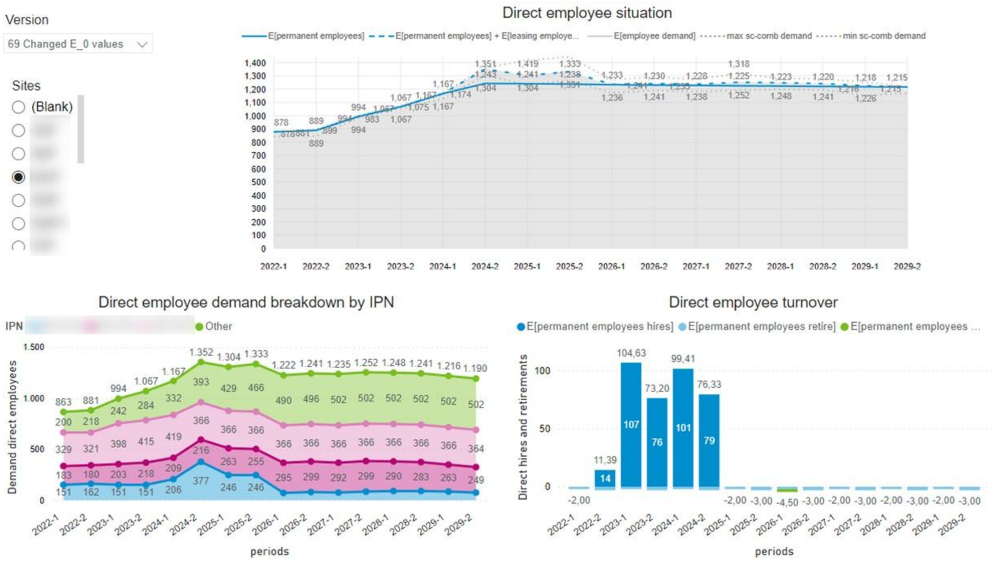

Figure A 30:LTPA Personnel Planning Overview

Solution Analysis Overview

To assess different solution options created using APVA with additional restrictions, a solution cost option overview is used, as shown in Figure A 31. It illustrates the mean change in costs compared to the original plan for a particular network. The costs are categorised based on APVA cost types and illustrated across periods.

Figure A 31: LTPA Solution Option Cost Overview

A9 Base Model for APVA & LTPA

A9.1 Calibration

The calibration assessment for APVA is shown in Figure A 32. It includes both calibrated parameters (CP) that can be directly drawn from some input and parameters that have to be inferred indirectly using a calibration function. Based on Equation 4-13, uncertainty, influence and opportunity are assessed for each parameter on a six-point Likert scale converted to $(0,1)$ ranges and combined to find the calibration priority. In particular, $order\_sizes$, $line\_OEE$, $cycle\_time$, and $feature\_costs$ are found to have the highest priority.

Calibrated Parameters	Category	Uncertainty	Influence	Opportunity	Calibration Priority
CP01 order_sizes	Orders	5	5	5	**0.512**
CP02 line_OEE	Line	4	4	4	**0.216**
CP03 cycle_time	Product	3	4	5	**0.192**
CP04 feature_costs	Line	5	4	3	**0.192**
CP05 fix_costs per line	Production System	3	4	4	**0.144**
CP06 var_cost per line	Production System	3	4	4	**0.144**
CP07 inb_log_costs	Logistics	4	3	4	**0.144**
CP08 max_capacity	Line	3	4	4	**0.144**
CP09 required_features	Product	2	5	5	**0.128**
CP10 line_features	Line	2	5	5	**0.128**
CP11 outb_log_costs	Logistics	3	3	4	**0.096**
CP12 standard_capacity	Line	2	4	5	**0.096**
CP13 customer_loc	Customers	2	3	5	**0.064**
CP14 underutilisation costs	Production System	4	3	2	**0.048**
CP15 overutilisation costs	Production System	4	3	2	**0.048**
CP16 fixed_allocation	Orders	2	3	4	**0.048**
CP17 fixed_vol_share	Orders	2	3	4	**0.048**
CP18 line_release_costs	Releases	3	2	4	**0.048**
CP19 site_release_costs	Releases	3	2	4	**0.048**
CP20 line_releases	Releases	2	2	6	**0.040**
CP21 site_releases	Releases	2	2	6	**0.040**
CP22 var_cost change rate	Production System	5	2	2	**0.032**
CP23 possible_upgrades	Line	3	3	2	**0.032**
CP24 line_site_link	Production Site	1	6	6	**0.000**

Figure A 32: Calibration Assessment for APVA

Based on this assessment possible calibration services (CS) for APVA are conceptualised as shown in Table A 42. The characteristics of the services are chosen based on the properties of the calibrated parameters. The desirability of these services is assessed as part of the implementation procedure introduced in 4.5.2.4.

Table A 42: Conceptualised Calibration Services for LTPA

Calibration Service	Data Demands Served	Data Source	Type
CS01	line_OEE	MES	ex-ante
CS02	cycle_time	MES	rule-based
CS03	feature_costs	ERP	on demand
CS04	fix_costs per line	MES	frequency

A10 Data Acquisition for LTPA & APVA

A10.1 Data Acquisition Strategies

In Table A 43, the considered data acquisition strategies are displayed. They are the result of the data demands from APVA and LTPA. Where applicable, multiple options are considered. In the following, the relevant considerations are discussed.

Table A 43: Overview of Data Acquisition Strategies Considered

Acquisition Strategy	Data Demands Served	Data Collection Methods	Synchro-nisation	Preprocessing Methods
AS01	Material Prices	Structuring from xlsx-File	on demand	Imputation, Schema Matching, Dimensionality Reduction
AS02	Material Prices	Interface with ERP	on demand	Imputation, Schema Matching, Dimensionality Reduction
AS03	Order Volumes and Likelihoods	Interface with Sales IS	on demand	Imputation, Advanced Transformation
AS04	Machine Utilisa-tions	Interface with Produc-tion Data Lake	frequency based	Imputation, Noise Reduction, Advanced Trans-formation
AS05	Technical Ca-pacity	Interface with Produc-tion Data Lake	frequency based	Imputation, Advanced Transformation
AS06	Variable Cost	Interface with ERP	frequency based	Imputation, Advanced Transformation
AS07	Fix Cost	Interface with ERP	frequency based	Imputation, Advanced Transformation
AS08	Logistic Cost	Interface with Logis-tics Planning System	change-based	Imputation, Schema Matching, Advanced Transformation
AS09	Station Capabil-ity	Structuring from xlsx-File	on demand	Imputation, Schema Matching, Advanced Transformation
AS10	Product Fea-tures	Interface with ERP	on demand	Imputation, Schema Matching, Advanced Transformation
AS11	Station Capabil-ity	Interface with MES	frequency based	Imputation, Schema Matching, Noise Reduc-tion, Advanced Transformation
AS12	DD02 Site Area	Structuring from xlsx-File	on demand	Imputation, Schema Matching, Advanced Transformation
AS13	DD02 Site Area	Interface with ERP	on demand	Imputation, Schema Matching, Advanced Transformation
AS14	Line (Re-)Con-struction Costs and Times	Interface with ERP	on demand	Imputation, Schema Matching, Noise Reduc-tion, Advanced Transformation
AS15	Process Times	Interface with MES	on demand	Imputation, Noise Reduction, Schema Match-ing, Advanced Transformation, Discretisation
AS16	DD03-DD07 Personnel Data	Structuring from an xlsx-file	on demand	Schema Matching, Advanced Transformation

- Material prices can be acquired in a semi-automated or fully automated manner. In both cases a demand-based acquisition is preferable, as the change frequencies are very high and a low impact on decision time is expected. In both cases, the data has to be generally cleaned, matched to the desired schema, and reduced to the corresponding values for the entire product.

- Order volumes and likelihoods could be drawn directly from the sales IS whenever planning runs occur. Especially likelihoods have to be transformed for APVA to initiate MCS of demand scenarios.
- Machine utilisation can be drawn from the organisations production data lake. This can be done independently of planning times. It involves a degree of imputation, noise reduction and transformation to ensure consistent values across a range of different sites.
- Technical capacity, i.e., nominal capacity for products based on cycle times and shift models can be drawn from the data lake with a set frequency as well. Some imputation and transformation steps are necessary.
- Variable and fixed costs can both be drawn from ERP. However, only costs for existing lines can be directly imported. To minimise preprocessing effect on decision times this can be done frequency-based avoiding frequent updates or waiting times. Both require imputation and transformation.
- Logistic costs can be inferred from the logistics planning system. This is currently done using a file transfer but could be fully connected. As updates to these costs are user driven and often require new planning, a change-based updating is sensible. Imputation, schema matching, and transformation are necessary.
- Station capabilities can either be determined semi-automated using a file-based transfer or directly from MES. For the former demand-based updating is preferable, as planners have to intervene manually, for the latter, frequency updating can be applied. Both require several preprocessing steps.
- Product features can likely be determined using the ERP, though manual intervention may be required. Thus, on demand updating is chosen. It requires imputation, schema matching and advanced transformation.
- Site Area can also be gathered in semi-automatic manner or automatic from the ERP. As both could require some degree of user intervention, on-demand updating is proposed. Both require imputation, schema matching and advanced transformation.
- Line construction or reconstruction costs can be drawn from ERP but require human intervention to interpret. Thus on-demand updating is chosen. Several preprocessing steps are necessary.

- Process times can be drawn from MES, but due to lacking available records from different generations of machines, human intervention may be necessary, leading to on-demand updating. The AS also requires several preprocessing steps.
- Personnel data can be structured from an xlsx file to eliminate additional manual processing steps, without the need for a full interface. For this schema matching and transformation are necessary.

A10.2 Data Acquisition Assessment

In the following the assessment of the data acquisition strategies is discussed. Table A 44 shows the considered values for all considered data acquisition strategies introduced in Appendix A10.1. The estimates for the set-up time are based on the implementation resources discussed in Appendix A11.4 and estimations for the required effort of each resource.

Table A 44: Overview of Data Acquisition Strategy Assessments

Data Acquisition Strategy (AS)	**Set-Up Time Estimate [m]**	**Cost Estimate [€]**	**Accuracy**	**Timeliness**	**Consistency**	**Completeness**	**Acquisition Time [d]**
AS01	1	14,000	0.8	0.7	0.7	0.8	2±1
AS02	2	36,000	0.9	0.9	0.9	0.9	
AS03	2	25,000	1	1	1	1	
AS04	1	24,000	1	1	1	1	
AS05	1	24,000	1	1	1	1	
AS06	2	18,000	1	1	1	1	
AS07	2	18,000	1	1	1	1	
AS08	20	107,000	1	1	1	1	
AS09	1	22,000	0.8	0.7	0.7	1	1±0.5
AS10	1.5	53,000	1	1	1	1	
AS11	2.25	66,000	1	1	1	1	
AS12	2	21,000	0.8	0.7	0.6	1	3±2
AS13	4	50,000	0.8	0.8	0.8	1	
AS14	2	35,000	1	1	1	1	
AS15	2	25,000	0.85	0.9	0.8	0.8	
AS16	2,5	23,000	0.95	0.9	0.75	0.85	1±0.5

A11 Organisational Integration in the Validation Case

Table A 45: Symbols Used in Appendix A11

Symbol	Description	Unit
α	Application-type	
A	Set of all application types under consideration	
π	Decision-situation	
Π	Set of all decision situations under consideration	
ϕ	Weighting exponent used when calculating objective weights (chosen as 1.6)	
b	Objective	
B	Set of objectives	
j	decision-situation characteristic (DC)	
$J^{(DS)}$	Set of decision-situation characteristics (DS)	
$v_{\pi,j}^{(IV)}$	Value of characteristic j for decision situation π	
$v_{b_1,b_2}^{(OB)}$	Evaluation of objective b_1 compared with b_2	
$w_{j,\alpha}^{(ACI)}$	Influence weight of characteristic j on application type α (application-characteristic influence ACI, scaled $-1 \dots 1$)	
$w_{b_1}^{(OB)}$	Weight assigned to objective b_1	
$W_{\pi,\alpha}^{(AT)}$	Utility of application type α in decision situation π(application-type utility AT)	

A11.1 Application Types

In the following possible application types for both APVA and LTPA are discussed. This assessment consists of a simple equally weighted utility analysis, where the utility $W_{m,\alpha}^{(AT)}$ of a particular application type (AT) α for a decision situation π is assessed as

$$W_{\pi,\alpha}^{(AT)} = \frac{\sum_{j\in J^{(DS)}}\left(w_{j,\alpha}^{(ACI)} v_{\pi,j}^{(IV)}\right)}{\sum_{j\in J^{(DS)}}\left(\left|w_{j,\alpha}^{(ACI)}\right|\right)} \; \forall \alpha \in A, \pi \in \Pi \qquad \textit{Equation A 139}$$

where $j \in J^{(DS)}$ are the decision situation characteristics (DC), $v_{\pi,j}^{(IV)}$ are the corresponding values for π, and $w_{j,\alpha}^{(ACI)}$ denotes the influence of j on α on a scale from -1 to 1. This assessment serves as an indication which application types are particularly interesting but may be overruled by other considerations.

APVA

Using the APVA assessment from Appendix A6 influence flows for each AT are derived and shown in Table A 46.

Table A 46: Assessment of Application Types for APVA

Conditional Influences		AT01	AT02	AT03	AT04	AT05	AT06	AT07	AT08	AT09	AT10
DC01	System Linearity	0	0	0.6	0.3	0.3	0.3	0	0	0	0
DC02	Number of Decision Variables	0	0.5	1	0.5	0.5	0.5	0	0	0	0
DC03	System Expertise	0.3	0.3	0	0.3	0.3	0	0	0	0.6	-0,3
DC04	Uncertainty	0	0	0	0	0.2	0.2	0.2	0	0.2	0
DC05	Decision Frequency	0	0.3	0.6	0.6	0.6	0	0	0	0.3	0
DC06	Decision Routine	0	0.3	0.6	0.3	0.3	0.3	0	0	0	0
DC07	Development Capabilities	0	0.3	0.6	0.3	0.3	0.6	0.6	0.6	0.6	0,6
DC08	Perspective Diversity	-0.1	-0.1	0	0	-0.1	0	0	-0.1	-0.2	-0,2
DC09	Achievable Accuracy	0	0	0.6	0.3	0.3	0.3	0.3	0.3	0.3	0
DC10	Objective Quantifiability	0.3	0.3	0.6	0.3	0.3	0.6	0.3	0	0	0
DC11	Data Acquisition Intensity	0	0	0.1	0	0	0.1	0.1	0.1	0.1	0
DC12	Time Horizon	0.1	0.1	-0.2	0	0.1	0	0.1	0	0.1	0
DC13	Decision Time	0.1	0.1	-0.2	-0.1	-0.1	-0.1	-0.1	0	-0.1	0
DC14	Computing Capabilities	0	0	0.6	0.3	0.6	0.6	0.6	0	0.6	0
DC15	Desired Explainability	-0.1	-0.1	0.1	-0.1	-0.1	0	0	-0.2	-0.2	-0,2
DC16	Model Expertise	0.1	0.1	0	0.1	0.2	0.1	0.1	0.1	0.1	0
Result		**0.20**	**0.38**	**0.45**	**0.48**	**0.39**	**0.47**	**0.37**	**0.20**	**0.27**	**-0.03**

The results show that the APVA decision situation is particularly suited to rule-based reactions (AT02), scheduled planning decisions (AT03, AT04, AT05) and monitoring (AT06, AT07). The existing implementation of APVA is best described as AT04. These results are relatively intuitive, as the relative frequency of APVA, its high number of decision variables and the objective quantifiability aid those assessments. The considerable development capacities also enable more development intensive ATs like AT03, AT06, and AT07. AT10 is generally viewed negatively in this assessment. However, this may change if users with drastically lower system expertise are considered, and the desired explainability is higher. Thus, AT19 still be considered for the determination of implementation directions.

LTPA

In the following possible ATs for LTPA are discussed based on the DC assessment in Appendix A7. The results and influence flows are shown in Table A 47.

Table A 47: Assessment of Application Types for LTPA

Conditional Influences		AT01	AT02	AT03	AT04	AT05	AT06	AT07	AT08	AT09	AT10
DC01	System Linearity	0	0	0.2	0.1	0.1	0.1	0	0	0	0
DC02	Number of Decision Variables	0	-0.1	-0.2	-0.1	-0.1	-0.1	0	0	0	0
DC03	System Expertise	0.1	0.1	0	0.1	0.1	0	0	0	0.2	-0,1
DC04	Uncertainty	0	0	0	0	0.6	0.6	0.6	0	0.6	0
DC05	Decision Frequency	0	0.1	0.2	0.2	0.2	0	0	0	0.1	0
DC06	Decision Routine	0	0.1	0.2	0.1	0.1	0.1	0	0	0	0
DC07	Development Capabilities	0	0.3	0.6	0.3	0.3	0.6	0.6	0.6	0.6	0,6
DC08	Perspective Diversity	0.3	0.3	0	0	0.3	0	0	0.3	0.6	0,6
DC09	Achievable Accuracy	0	0	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0
DC10	Objective Quantifiability	0.1	0.1	0.2	0.1	0.1	0.2	0.1	0	0	0
DC11	Data Acquisition Intensity	0	0	0.3	0	0	0.3	0.3	0.3	0.3	0
DC12	Time Horizon	0.1	0.1	-0.2	0	0.1	0	0.1	0	0.1	0
DC13	Decision Time	0.1	0.1	-0.2	-0.1	-0.1	-0.1	-0.1	0	-0.1	0
DC14	Computing Capabilities	0	0	0.6	0.3	0.6	0.6	0.6	0	0.6	0
DC15	Desired Explainability	0.3	0.3	-0.3	0.3	0.3	0	0	0.6	0.6	0,6
DC16	Model Expertise	0.1	0.1	0	0.1	0.2	0.1	0.1	0.1	0.1	0
Result		**0.31**	**0.27**	**0.15**	**0.23**	**0.31**	**0.33**	**0.40**	**0.50**	**0.42**	**0.49**

The results show a broad applicability of LTPA across a range of applications. The initial application type can be described as a combination of AT06, when assessing deviations and AT02 when addressing those deviations. As the analysis shows, similar tools may also be useful in an individual reaction, for example due to changes in strategic premises, in contingent realisation (AT05), in risk monitoring (AT07) and general teaching use (AT08, AT09, AT10). This aligns with the high degree of abstraction, and corresponding uncertainty.

A11.2 Initial Development

The initial development comprises the creation of APVA as described by Brützel et al. (2025). This development is not part of this work, but the starting point for further development characterised in 5.5.2. This section briefly discusses the selection of APVA as the initial DSS as per the initial development considerations outlined in 4.5.2.1. Specifically, Table A 48 shows an assessment of APVA in regard to the selection criteria for an initial DSS. For the opportunity criteria, the situation present at the time of APVA development is considered.

Table A 48: Assessment of APVA as an Initial DSS

Type	Criterion	Characterisation	Evaluation
PNC Task	Result Improvement Potential	The process is error prone due to the high number of individual decisions and system complexity. The optimisation can improve decision quality significantly on average.	++
	Process Improvement Potential	The model can reduce decision-making time by multiple days.	++
	Data Requirements	Data from several distinct sources is necessary for the decision. This data is already mostly aggregated in standardised forms for the decision process.	-
	Scalability	Similar decisions are made across all IPNs of the organisations, following a standardised structure. Scalability is high.	++
	Complexity	The system complexity is mainly driven by the number of elements and decision variables. The relations between those elements are relatively simple.	+
	Structuredness	The decision is relatively well structured, following objectives that can be clearly defined as well as decision rules.	+
	Decision Frequency	These decisions are made with moderate frequency	
Opportunity	User Capacity	Multiple users with moderate to high system and model knowledge where available at the time of development.	+
	Developer Capacity	Normal developer availability.	
	Existing Model	The work could build upon some early modelling approaches for the same decision, somewhat simplifying the DSS creation.	+
	Existing Deficit	No specific deficit was present, but the high overall effort for the decision process was known.	-
	Available Database	No database suitable for model creation existed.	--

Overall, the assessment of APVA is positive. Even though no systematic assessment of initial options was performed before implementation, the PVA process would likely have been one if not the primary candidate due to the high scalability and the suitability for model-based decision making.

A11.3 Development Portfolio

In Table A 49 the full development portfolio is shown, based on the creation procedure proposed in 4.5.2.3. Only items 1-33 are selected for the subsequent roadmap generation due to the maturity of assessment.

Table A 49: Available Implementation Items and Selection for Roadmapping

Layer	Development Direction	Identified Items	
Data Acquisition	Data Scope	II15	Material Price Import Form (AS01)
		II16	Automatic Material Price Import from ERP System (AS02)
		II17	Sales Forecast Import from Sales IS (AS03)
		II19	Machine Utilisations from Production Data Lake (AS04)
		II20	Technical Capacity Import from Production Data Lake (AS05)
		II21	Variable Cost Import from ERP System (AS06)
		II22	Fix Cost Import from ERP System (AS07)
		II23	Automatic Logistic Cost Import from Logistics Planning System (AS08)

Layer	Development Direction	Identified Items	
		II24	Station Capability Import Form (AS09)
		II25	Product Feature Import from BOM (AS10)
		II26	Automatic Station Capability Import (AS11)
		II28	Site Area Import Form (AS12)
		II29	Automatic Site Area Import (AS13)
		II30	Historical Change Data Import (AS14)
		II48	Process Times Import (AS15)
		II49	Personnel Data Form (AS16)
Base Model	Function Scope	II31	APVA in Database
		II32	LTPA in Database
		II13	Purchase Fineplanning in Database
		II34	Logistics Planning System
	Data Model	II35	Detailed Logistics Information
		II36	Area Plans of Sites and Lines
		II37	Demographic Information for Site Personnel
	Function Development	II12	Versioning
		II38	Calibration of Investments (CS03)
		II39	Calibration of OEE Curves for (New) Lines (CS01)
		II27	Calibration of Fix and Change Costs for APVA (CS04)
		II50	Calibration of Cycle Times (CS02)
Application	Application Scope	II08	APVA: Explorative Planning
		II09	APVA: User Training System
		II11	APVA: Automated Monitoring
		II40	LTPA: User Training System
	Application Type	II03	APVA: Allocation Planning for Multiple Echelons
		II05	APVA: Reconfiguration Extension
		II06	APVA: Area Planning Extension
		II41	APVA: Contingency Planning
		II42	LTPA: Individual Reactive Strategic Planning
		II14	Purchase Fineplanning: Supplier Price Scenarios
	Application Methodology	II43	APVA: Reformulation as a Dynamic Optimisation Problem
		II07	APVA: Dynamic OEE
		II44	APVA: Multi-Objective Optimisation with Greenhouse Gas Emissions
		II10	APVA: Interactive DoE
		II33	APVA: Enhanced Error Correction
		II45	LTPA: Integrated Employee Planning Based on Demographics
		II46	LTPA: Two-Dimensional Area Planning
		II47	LTPA: Metaheuristic Optimisation of Resolution Options for Deviations
	Application Creations	II01	Multi-Echelon Network Configuration
		II02	Purchase Fineplanning
		II04	Long-Term Planning Assistant

A11.4 Development Roadmap

In the following, the roadmap development process is shown. Specific values and value distributions for resources, items, and enhancing dependencies are not shown here.

Weights

The objective category weights are determined using an adapted pairwise comparison where the weight $w_{b_1}^{(OB)}$ of each objective $b_1 \in B$ is calculated as follows:

$$w_{b_1}^{(OB)} = \frac{\left(\sum_{b_2 \in B} v_{b_1,b_2}^{(OB)}\right)^{\phi}}{\sum_{b_3 \in B}\left(\sum_{b_2 \in B} v_{b_2,b_3}^{(OB)}\right)^{\phi}} \quad \forall b_1, b_2, b_3 \in B \qquad \text{Equation A 140}$$

where $v_{b_1,b_2}^{(OB)}$ denotes the evaluation of b_1 compared to b_2 and ϕ denotes a weighing factor to amend the distribution of weights. In this case $\phi = 1.6$ is chosen which yields an emphasis on the most important objectives while maintaining a consideration of less important objectives. The comparison and its results are shown in Figure A 33.

Category	Capital Value	Decision Quality	Decision Speed	Decision Transparency	Reaction Speed	System Knowledge	Learning Speed	Employee Satisfaction	User Capacity	adjustedSum	Weight
Capital Value		2	2	2	2	2	2	2	2	101.96	0.26
Decision Quality	0		2	2	2	2	2	2	2	84.45	0.21
Decision Speed	0	0		2	2	2	2	2	2	68.20	0.17
Decision Transparency	0	0	0		0	1	1	1	1	17.58	0.04
Reaction Speed	0	0	0	2		2	2	2	2	53.30	0.13
System Knowledge	0	0	0	1	0		1	1	1	17.58	0.04
Learning Speed	0	0	0	1	0	1		1	1	17.58	0.04
Employee Satisfaction	0	0	0	1	0	1	1		1	17.58	0.04
User Capacity	0	0	0	1	0	1	1	1		17.58	0.04
										395.81	**1**

Figure A 33: Pairwise Comparison of Objectives for Roadmap Generation

Resources

The resource types for development include several distinct types of developers as well as user groups necessary for the development of some of the items. The resource types and their classification are shown in Table A 50.

Table A 50: Development Resources for Roadmap Generation

Resource Type	Resource Category
Architect	Development
Project Manager	Development
Pilot Developer	Development
Developer	Development
IPN Planner	User

Resource Type	Resource Category
Site Management	User
Logistics	Support
Controlling	Support
Sales	Support
IT Support	Support
Purchasing	User
MFC Planner	User

Categorical Dependencies

In total 59 categorical dependencies are identified. These dependencies, the dependent items and fulfilling items are shown in Table A 51.

Table A 51: Categorical Dependencies in Roadmap Generation

Dependency		Dependent Item	Fulfilling Items
1	APVA->Network Config	1	18
2	APVA->Fineplanning	3	18
3	Fineplanning->Network Configurator	1	3
4	Purchase -> Network Configurator	1	2
5	APVA->LTPA	4	18
6	APVA->Recon Extension	5	18
7	APVA->Area Extension	6	18
8	APVA->Dynamic OEE	7	18
9	APVA->Shadow	8	18
10	APVA->Training	9	18
11	APVA->Interactive DoE	10	18
12	APVA-> Monitoring	11	18
13	Station Capabilities -> APVA Recon	5	24, 26
14	Site Area Import -> LTPA	4	28, 29
15	Site Area Import -> Area Extension	6	28, 29
16	Change Data Import -> Change Calibration	27	30
17	Material Price Data -> Purchasing in SQL	13	15, 16
18	SQL->Purchasing in SQL	13	31
19	SQL->LTPA in SQL	32	31
20	Automatic Utilisation -> APVA Monitoring	11	19
21	Automatic TEC -> APVA Monitoring	11	20
22	Automatic Variable Costs -> APVA Monitoring	11	21
23	Automatic Fix Costs -> APVA Monitoring	11	22
24	Automatic Logistics Costs -> APVA Monitoring	11	23
25	Automatic Capabilities -> APVA Monitoring	11	25
26	Automatic Station Capabilities -> APVA Monitoring	11	26
27	Automatic Material Data -> APVA Monitoring	11	16
28	APVA->APVA Error Corrections	33	18
29	Shadow APVA -> Monitoring	11	8
30	SQL -> Monitoring	11	31

	Dependency	Dependent Item	Fulfilling Items
31	SQL -> Versioning	12	31
32	Versioning -> LTPA in SQL	32	12
33	Versioning -> APVA Recon	5	12
34	Versioning -> APVA Dynamic OEE	7	12
35	Versioning -> APVA Training	9	12
36	Versioning -> Shadow APVA	8	12
37	Versioning -> Interactive DoE	10	12
38	Versioning -> APVA Monitoring	11	12
39	Versioning -> Purchasing in SQL	13	12
40	Versioning -> Supplier Price Scenarios	14	12
41	Versioning -> Change Cost	27	12
42	LTPA in SQL -> LTPA	4	32
43	Automatic Util -> Dynamic OEE	7	19
44	Purchasing in SQL -> Supplier Price	14	13
45	Versioning -> APVA Error Corrections	33	12
46	APVA Error Correction -> Interactive DoE	10	33
47	APVA Error Correction -> APVA Monitoring	11	33
48	APVA Error Correction -> APVA Training	9	33
49	SQL -> Automatic Material Price	16	31
50	SQL -> Sales Data Import	17	31
51	SQL -> Automatic Util	19	31
52	SQL -> Automatic TEC	20	31
53	SQL -> Automatic Variable Costs	21	31
54	SQL -> Fix Costs	22	31
55	SQL-> Logistic Costs	23	31
56	SQL -> Aut. Capabilities	25	31
57	SQL -> Aut. Station Capabilities	26	31
58	SQL -> Area Import	29	31
59	SQL -> Historic Change Data	30	31

Enhancing Dependencies

102 enhancing dependencies are identified. These can be ‘discrete’, where fulfilment only depends on the presence of the enhancing items or quality driven, where the fulfilment evaluation function introduced in is used. The enhancing dependencies, enhanced items, enhancing items are shown in Table A 52.

Table A 52: Overview of Enhancing Dependencies in Roadmap Generation

	Dependency	Enhanced Item	Enhancing Items	Type
1	Error Correction -> APVA	18	33	discrete
2	Error Correction -> Shadow APVA	8	33	discrete
3	Error Correction -> LTPA	4	33	discrete
4	Error Correction -> APVA Fineplanning	3	33	discrete
5	SQL->APVA	18	31	discrete

Dependency		Enhanced Item	Enhancing Items	Type
6	SQL->Network Configurator	1	31	discrete
7	SQL->Area Extension	6	31	discrete
8	SQL->APVA Fineplanning	3	31	discrete
9	Hist. Change Import -> APVA	18	30	discrete
10	Hist. Change Import -> Recon Extension	5	30	discrete
11	Hist. Change Import -> Area Extension	6	30	discrete
12	Hist. Change Import -> APVA Monitoring	11	30	discrete
13	Hist. Change Import -> Shadow APVA	8	30	discrete
14	Hist. Change Import -> LTPA	4	30	discrete
15	Hist. Change Import -> Network Configurator	1	30	discrete
16	Site Area Import -> Area Extension	6	28, 29	quality-driven
17	Site Area Import -> LTPA	4	28, 29	quality-driven
18	Network Configurator->APVA	18	1	discrete
19	Calibration -> APVA	18	27	discrete
20	Calibration -> LTPA	4	27	discrete
21	Calibration -> Shadow APVA	8	27	discrete
22	Calibration -> APVA Monitoring	11	27	discrete
23	Calibration -> Network Configurator	1	27	discrete
24	Station Capabilities -> APVA	18	24, 26	quality-driven
25	Station Capabilities -> Recon	5	24, 26	quality-driven
26	Station Capabilities -> LTPA	4	24, 26	quality-driven
27	Station Capabilities -> Shadow APVA	8	24, 26	quality-driven
28	Station Capabilities -> Network Configurator	1	24, 26	quality-driven
29	Capabilities -> APVA	18	25	discrete
30	Capabilities -> Recon	5	25	discrete
31	Capabilities -> LTPA	4	25	discrete
32	Capabilities -> Shadow APVA	8	25	discrete
33	Capabilities -> Network Configurator	1	25	discrete
34	Logistic Costs -> APVA	18	23	discrete
35	Logistic Costs -> Recon	5	23	discrete
36	Logistic Costs -> LTPA	4	23	discrete
37	Logistic Costs -> Shadow APVA	8	23	discrete
38	Logistic Costs -> Network Configurator	1	23	discrete
39	Logistic Costs -> APVA Fineplanning	3	23	discrete
40	Logistic Costs -> Purchase Fineplanning	2	23	discrete
41	Fix Costs -> APVA	18	22	discrete
42	Fix Costs -> Recon	5	22	discrete
43	Fix Costs -> LTPA	4	22	discrete
44	Fix Costs -> Shadow APVA	8	22	discrete
45	Fix Costs -> Network Configurator	1	22	discrete
46	Fix Costs -> APVA Fineplanning	3	22	discrete
47	Fix Costs -> Purchase Fineplanning	2	22	discrete
48	Variable Costs -> APVA	18	21	discrete
49	Variable Costs -> Recon	5	21	discrete
50	Variable Costs -> LTPA	4	21	discrete

	Dependency	Enhanced Item	Enhancing Items	Type
51	Variable Costs -> Shadow APVA	8	21	discrete
52	Variable Costs -> Network Configurator	1	21	discrete
53	Variable Costs -> APVA Fineplanning	3	21	discrete
54	Variable Costs -> Purchase Fineplanning	2	21	discrete
55	TEC Import -> APVA	18	20	discrete
56	TEC Import -> Recon	5	20	discrete
57	TEC Import -> LTPA	4	20	discrete
58	TEC Import -> Shadow APVA	8	20	discrete
59	TEC Import -> Network Configurator	1	20	discrete
60	TEC Import -> APVA Fineplanning	3	20	discrete
61	Utilisation Import -> APVA	18	19	discrete
62	Utilisation Import -> Recon	5	19	discrete
63	Utilisation Import -> LTPA	4	19	discrete
64	Utilisation Import -> Shadow APVA	8	19	discrete
65	Utilisation Import -> Network Configurator	1	19	discrete
66	Utilisation Import -> APVA Fineplanning	3	19	discrete
67	Sales Data Import -> APVA	18	17	discrete
68	Sales Data Import -> Recon	5	17	discrete
69	Sales Data Import -> LTPA	4	17	discrete
70	Sales Data Import -> Shadow APVA	8	17	discrete
71	Sales Data Import -> Network Configurator	1	17	discrete
72	Sales Data Import -> APVA Fineplanning	3	17	discrete
73	Sales Data Import -> Purchase Fineplanning	2	17	discrete
74	Material Price Import -> APVA	18	15, 16	quality-driven
75	Material Price Import -> Recon	5	15, 16	quality-driven
76	Material Price Import -> LTPA	4	15, 16	quality-driven
77	Material Price Import -> Shadow APVA	8	15, 16	quality-driven
78	Material Price Import -> Network Configurator	1	15, 16	quality-driven
79	Material Price Import -> APVA Fineplanning	3	15, 16	quality-driven
80	Material Price Import -> Purchase Fineplanning	2	15, 16	quality-driven
81	Versioning -> APVA	18	12	discrete
82	Versioning -> Network Config	1	12	discrete
83	Versioning -> APVA Fineplanning	3	12	discrete
84	Versioning -> Purchase Fineplanning	2	12	discrete
85	Interactive DoE -> APVA	18	10	discrete
86	Interactive DoE -> Shadow APVA	8	10	discrete
87	Interactive DoE -> Network Configurator	1	10	discrete
88	Dynamic OEE -> APVA	18	7	discrete
89	Dynamic OEE -> Recon	5	7	discrete
90	Dynamic OEE -> LTPA	4	7	discrete
91	Dynamic OEE -> Shadow APVA	8	7	discrete
92	Dynamic OEE -> Network Configurator	1	7	discrete
93	Dynamic OEE -> APVA Fineplanning	3	7	discrete
94	Dynamic OEE -> Purchase Fineplanning	2	7	discrete
95	Area Extension -> APVA	18	6	discrete

Dependency		Enhanced Item	Enhancing Items	Type
96	Area Extension -> Shadow APVA	8	6	discrete
97	Recon Extension -> APVA	18	5	discrete
98	Recon Extension -> Shadow APVA	8	5	discrete
99	Purchasing in SQL -> Purchasing Fineplanning	2	13	discrete
100	Purchasing in SQL -> Network Config	1	13	discrete
101	Price Scenarios in Purchasing -> Purchasing Fineplanning	2	14	discrete
102	Price Scenarios in Purchasing -> Network Config	1	14	discrete

Results

The resulting roadmaps including the corresponding preference ranges and combination IDs are shown in Table A 53.

Table A 53: Resulting Roadmaps with Corresponding Preference Ranges and Item Combinations

Road map Nr	Lower Limit [°]	Upper Limit [°]	Included Combinations
1	0.00	3.61	259790, 259786, 184044, 183584, 369797, 369741, 369495, 474074, 474073, 474057, 473683, 460559, 460514, 460372, 489618, 489614, 489590, 489094, 489092
2	3.61	22.58	259790, 172719, 172717, 169953, 369797, 369741, 369495, 474074, 474073, 474057, 473683, 460559, 460514, 460372, 489618, 489614, 489590, 489094, 489092
3	22.58	26.01	176208, 172719, 172717, 169953, 369797, 369741, 369495, 474074, 474073, 474057, 473683, 460559, 460514, 460372, 489618, 489614, 489590, 489094, 489092
4	26.01	30.25	176208, 172719, 172717, 169953, 369797, 369741, 369495, 474074, 474073, 474057, 473683, 460559, 460514, 460372, 505476, 489618, 489614, 489590, 489094, 489092
5	30.25	31.47	176208, 172719, 172717, 169953, 369797, 369741, 369495, 474074, 474073, 474057, 460898, 460559, 460514, 460372, 505476, 489618, 489614, 489590, 489094, 489092
6	31.47	43.48	176208, 172719, 169955, 169953, 369797, 369741, 369495, 474074, 474073, 474057, 460898, 460559, 460514, 460372, 505476, 489618, 489614, 489590, 489094, 489092
7	43.48	45.67	176208, 172719, 172702, 169964, 169962, 369815, 369750, 369497, 474090, 474089, 474081, 460922, 460583, 460536, 460455, 510084, 510082, 504970, 489104, 489096
8	45.67	47.24	176208, 172719, 172702, 169964, 169962, 369815, 369750, 369497, 474090, 474089, 474081, 460922, 460583, 460536, 460455, 510084, 510082, 504970, 494476, 489104, 489096
9	47.24	51.33	176208, 172719, 172702, 169964, 169962, 369880, 369750, 369497, 474090, 474089, 474081, 460922, 460583, 460536, 460455, 510084, 510082, 504970, 494476, 489104, 489096
10	51.33	53.14	176208, 172719, 169955, 169953, 369797, 369741, 369495, 474074, 474073, 460914, 460898, 460559, 460514, 460372, 505476, 489618, 489614, 489590, 489094, 489092
11	53.14	55.76	172719, 169955, 169953, 369797, 369741, 368419, 470115, 460915, 460914, 460898, 460559, 460514, 460372, 505476, 489618, 489614, 489590, 489094, 489092
12	55.76	60.79	172719, 169955, 169953, 369797, 369741, 368419, 470115, 460915, 460914, 460898, 460559, 460514, 460372, 505476, 494990, 489618, 489614, 489590, 489094, 489092
13	60.79	69.69	172719, 169955, 169953, 369797, 368435, 368419, 470115, 460915, 460914, 460898, 460559, 460514, 460372, 505476, 494990, 489618, 489614, 489590, 489094, 489092
14	69.69	71.91	172719, 169955, 169953, 368515, 368435, 368419, 470115, 460915, 460914, 460898, 460559, 460514, 460372, 505476, 494990, 489618, 489614, 489590, 489094, 489092
15	71.91	75.75	172719, 172702, 169964, 169962, 369815, 368444, 368421, 470131, 460931, 460930, 460922, 460583, 460536, 441000, 495042, 489670, 489622, 489598, 489098, 489096
16	75.75	79.96	172719, 172702, 169964, 169962, 369815, 368444, 368421, 470131, 460931, 460930, 460922, 460583, 441040, 411522, 489682, 489634
17	79.96	82.97	172719, 172702, 169964, 169962, 369880, 369750, 411301, 411118, 408127, 407970, 407969, 407962, 489682, 489634
18	82.97	84.41	172702, 169964, 169962, 369880, 369750, 411301, 411118, 408127, 407970, 407969, 407962, 489682, 489634
19	84.41	90.00	172702, 169964, 169962, 369880, 369750, 411301, 411118, 408127, 407970, 407963, 407962, 489682, 489634

Figure A 34 shows the realisation time for each implementation item across the roadmaps. It is apparent, that some items are chosen at the beginning across the roadmaps whereas differ by the roadmap chosen. Overall, most items from the development portfolio are considered beneficial and should be implemented. The roadmaps also allow for a prioritisation of items in time.

Roadmaps \ Items	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
1	38.4	38.4	38.4	16.0	10.1	26.5	19.8	5.7			43.8	5.7				24.2	28.8	18.5	40.8	11.3	17.3	28.0	10.1	22.2	39.9	46.1	16.0		7.2	5.7	16.0	20.9
2	38.4	38.4	38.4	10.9	14.9	26.5	19.8	5.7			43.8	5.7				24.2	28.8	18.5	40.8	16.0	17.3	28.0	14.9	22.2	39.9	46.1	10.9		12.1	5.7	10.9	20.9
3	38.4	38.4	38.4	10.3	14.9	26.5	19.8	10.9			43.8	10.3				24.2	28.8	18.5	40.8	16.0	17.3	28.0	14.9	22.2	39.9	46.1	10.3		12.1	10.3	10.3	20.9
4	38.4	38.4	32.6	10.3	14.9	26.5	19.8	10.9			43.8	10.3				24.2	28.8	18.5	40.8	16.0	17.3	28.0	14.9	22.2	39.9	46.1	10.3		12.1	10.3	10.3	20.9
5	38.4	38.4	32.6	10.3	14.9	24.7	19.8	10.9			43.8	10.3				26.5	28.8	18.5	40.8	16.0	17.3	28.0	14.9	22.2	39.9	46.1	10.3		12.1	10.3	10.3	20.9
6	38.4	38.4	32.6	10.3	13.7	24.7	19.8	10.9			43.8	10.3				26.5	28.8	18.5	40.8	16.0	17.3	28.0	13.7	22.2	39.9	46.1	10.3		14.9	10.3	10.3	20.9
7	44.6	44.6	39.2	10.3	15.0	25.9	21.0	10.9			33.4	10.3				27.7	45.3	19.7	30.2	17.2	18.4	29.0		23.4	12.9	35.8	10.3		16.2	10.3	10.3	22.1
8	44.6	43.3	39.2	10.3	15.0	25.9	21.0	10.9			33.4	10.3				27.7	45.3	19.7	30.2	17.2	18.4	29.0		23.4	12.9	35.8	10.3		16.2	10.3	10.3	22.1
9	44.6	43.3	39.2	10.3	15.0	25.9	21.0	10.9			33.4	10.3				27.7	45.3	19.7	30.2	18.4	17.2	29.0		23.4	12.9	35.8	10.3		16.2	10.3	10.3	22.1
10	38.4	38.4	32.6	10.3	13.7	23.3	19.8	10.9			43.8	10.3				26.5	28.8	18.5	40.8	16.0	17.3	28.0	13.7	24.7	39.9	46.1	10.3		14.9	10.3	10.3	20.9
11	38.4	38.4	32.6	10.9	13.7	19.9	22.3	10.9			43.8	10.9				26.5	28.8	21.0	40.8	16.0	17.3	28.0	13.7	24.7	39.9	46.1	10.9		14.9	10.9	10.9	23.3
12	38.4	37.5	32.6	10.9	13.7	19.9	22.3	10.9			43.8	10.9				26.5	28.8	21.0	40.8	16.0	17.3	28.0	13.7	24.7	39.9	46.1	10.9		14.9	10.9	10.9	23.3
13	38.4	37.5	32.6	10.9	13.7	18.7	22.3	10.9			43.8	10.9				26.5	28.8	21.0	40.8	16.0	19.9	28.0	13.7	24.7	39.9	46.1	10.9		14.9	10.9	10.9	23.3
14	38.4	37.5	32.6	10.9	13.7	17.8	22.3	10.9			43.8	10.9				26.5	28.8	21.0	40.8	18.7	19.9	28.0	13.7	24.7	39.9	46.1	10.9		14.9	10.9	10.9	23.3
15	38.6	37.7	32.9	10.9	15.0	20.0	23.6	10.9			43.1	10.9				27.7	39.3	22.2	40.2	17.2	21.1	29.0		25.9	12.9	45.3	10.9		16.2	10.9	10.9	24.6
16	35.8	34.4	30.8	10.9	15.0	20.0	23.6	10.9				10.9				27.7	36.6	22.2		17.2	21.1			25.9	12.9		10.9		16.2	10.9	10.9	24.6
17	26.3	26.3	26.3	10.9	15.0	35.8	28.8	10.9				10.9				30.4	36.6	27.4		18.4	17.2			32.8	12.9		10.9		16.2	10.9	10.9	31.5
18	26.3	26.3	26.3	12.9	15.0	35.8	28.8	12.9				12.9				30.4	36.6	27.4		18.4	17.2			32.8	12.9		12.9		16.2	12.9	12.9	31.5
19	26.3	26.3	26.3	12.9	15.0	35.8	28.8	12.9				12.9				30.4	36.6	27.4		18.4	17.2			31.8	12.9		12.9		16.2	12.9	12.9	32.8

Figure A 34: Realisation Times of Implementation Items in Different Roadmaps [m]

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