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METHOD

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Robust planning of production networks at an automotive supplier

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ABSTRACT
As global trends like individualisation continue to drive significant changes in industrial production within international networks, it has become increasingly crucial for companies to maintain competitiveness through the efficient utilisation of resources. The rising complexity in production networks originates from an increasing number of constraints due to company-specific requirements, coupled with expanding networks that broaden the solution space, ultimately leading to prolonged planning processes. Furthermore, current planning tasks are predominantly performed manually, as the extensive efforts required for data acquisition often render the use of solution algorithms infeasible due to incomplete or inaccurate data. Therefore, this study explores robust planning of production networks, employing Monte–Carlo simulation and clustering for scenario generation, stochastic modelling concepts to tackle the mathematical problem, and utilising DT concepts for data integration at the network level.

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Production network configuration; robust planning; digital twin; scenario analysis; flexible production; SDG 9: Industry; innovation and infrastructure

Introduction

Product lifecycles in industries such as microprocessors, consumer electronics, personal computers, and automotive have become increasingly short in recent years (Becker, Stolletz, and Stäblein 2017). This has resulted in an increase in product variety and a higher number of production ramp-ups. Combined with increasing competition from new competitors in developing markets, this has resulted in a need for companies to reduce manufacturing costs by distributing production activities globally.

However, the constantly changing range of product variants and shortened product lifecycles contrast with the long-term and irreversible nature of network planning decisions. Thus, product-mix allocation (PMA), which means allocating products to global production network (GPN) entities while utilising and adapting global production structures and capacities is a complex task for companies. In real-world environments, production planning must therefore consider different sources and resulting influences of uncertainties (Table 1 – Requirement R1) such as the nondeterministic nature of demand. This nondeterministic nature has increased in recent years due to different global developments (Matthews et al. 2022). Accordingly, optimal supply chain and production configurations change for different realisations of demand (Govindan and Fattahi 2017). The predominant method used to quantify diverging demand in industries is scenario analysis. Therefore, extreme scenarios (best-/worst case) of the scenario funnel are usually depicted for ease of understanding for planners. The advantages of quantitative scenario analysis lie in the possibility of covering more extensive parts of the future space and thus increasing the robustness of a plan. The disadvantages compared to qualitative methods lie in the required probability estimates, the difficulty of explaining the results, and the high number of scenarios (Kosow and Gassner 2008).

As a promising strategy to cope with these uncertainties, companies tend to implement flexibility in their GPN (Table 1 – Requirement R2). Using flexibility potentials, e.g. redundancies like capacity buffers or flexibility strategies like multiple sourcing, flexibility allows to quickly adapt to the realisation of uncertainties and thus maintain a stable network performance (Peukert, Hörger, and Zehner 2023). The literature on production systems highlights product-mix and volume flexibility as the crucial types of flexibility (Hochdörffer et al. 2022). Volume flexibility of a production system is the ability to operate profitably at different overall production volumes (Sethi and Sethi 1990). Product-mix flexibility is characterised by the ability to produce multiple

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Table 1. Comparison of relevant approaches from the state of the art.

Category	Author (Year)	R1: Considering Demand Uncertainty in GPN Planning		R2: Modeling Flexibility in GPNs		R3: Systematic derivation of robust decisions in GPN			R4: Realisation of the model as a digital twin		
		Consideration of different impact factors	Systematic derivation of representative demand scenarios	Product mix flexibility	Volume flexibility	Model focus on Product-Mix Allocation in GPN	Robust decision support	Solution Approach	Digital representation of GPN (Digital Master DM)	Digital data for each GPN entity (Digital Shadow DS)	Continous synchronisation of DM and DS (Digital Twin DT)
Incorporation of demand uncertainty	Petropoulus & Siemens (2023)	○	◑	○	○	○	○	Statistical Model Slection	○	○	○
	Cuong et al. (2022)	◑	○	○	○	○	○	Systematic parameter variation	○	○	○
	Cuong et al. (2024)	◑	○	○	○	○	○	Fractional Brownian motion	○	○	○
	Bihlmaier, Koberstein & Obst (2009)	○	◑	◑	◑	◑	◑	Monte Carlo Simulation and Benders Decomposition	○	○	○
	Stähr, Englisch & Lanza (2018)	◑	◑	○	◑	○	◑	Monte Carlo Decision Problem and Backward Induction	○	○	○
	Santoso et al. (2005)	○	◑	○	○	◑	◑	Sample Average Approximation and Benders Decomposition	○	○	○
	Azaron, Venkatadri & Farhang Doost (2021)	○	◑	○	○	◑	●	Sample Average Approximation and ϵ-Constraint Method	○	○	○
	Buergin et al. (2019)	○	◑	◑	○	○	◑	K-Means	○	○	○
	Khatami, Mahootchi & Farahani (2015)	○	◑	○	○	●	◑	K-Means and Benders Decomposition	○	○	○
	Baringo & Conejo (2013)	◑	◑	○	○	○	◑	K-Means	○	○	○
Modeling flexible GPNs	Sethi & Sethi (1990)	○	○	●	●	○	○	-	○	○	○
	Bachlaus et al. (2008)	○	◑	○	◑	◑	●	Hybrid Taguchi Particle Swarm Optimization	○	○	○
	Lanza & Moser (2014)	●	◑	●	●	◑	◑	Dynamic Multi-Objective Optimization	○	○	○
	Hochdörffer et al. (2022)	○	◑	●	●	◑	●	Flexibility Constraints and Solver	○	○	○
Robust Decision Making in GPN	Lotfi et al. (2021)	○	◑	○	●	●	●	ϵ-Constraint Method, Lagrangian Relaxation, and Solver	○	○	○
	Fattahi (2020)	◑	◑	○	◑	◑	●	Benders Decomposition and Solver	○	○	○
	Govindan & Fattahi (2017)	◑	◑	○	○	◑	●	Latin Hypercube Sampling and Solver	○	○	○
	Bertsimas & Sim (2003)	○	◑	○	○	○	●	Multi-Policy Approximation Scheme	○	○	○
	Mulvey, Vanderbei & Zenios (1995)	○	○	○	○	○	●	ϵ-Constraint Method and Solver	○	○	○
Digital Twins of GPN	Bergmann, Straßburger & Schulze (2013)	○	○	○	○	○	○	Automatic Generation of Event Discrete Simulation	●	●	◑
	Gölzer et al. (2015)	◑	●	○	○	○	◑	Core Manufacturing Simulation Data Standard	◑	●	◑
	Bergman et al. (2011)	○	○	○	○	○	○	Automatic Generation of Event Discrete Simulation	●	●	◑
	Ivanov & Dolgui (2021)	○	○	○	○	○	◑	Digital Supply Chain Twin	●	●	●
	Milde & Reinhart (2022)	○	○	○	○	◑	◑	Automatic Generation of Event Discrete Simulation	●	●	●
This approach		●	●	●	●	●	●	Monte Carlo Simulation, K-Means, Principal Component Analysis, MILP, SQL	●	●	◑

distinct products at one site without major cost disadvantages. However, quantifying the impact of corresponding flexibility measures remains a major problem (Hochdörffer et al. 2022).

Together, taking into consideration both, uncertainty and flexibility, manual PMA in GPN becomes even more challenging. Therefore, companies increasingly use model-based decision support systems for GPN planning tasks to increase planning reliability and solution robustness in medium- and long-term planning (Table 1 – Requirement R3) (Melo, Nickel, and Saldanha-da-Gama 2009). The robustness of results compares several possible scenarios. The more minor the scenario-dependent deviations of the planning result and its decisions are, the more result-robust the plan is (Scholl 2001).

In addition, due to the ever faster-changing environment of GPN, also medium- and long-term decisions must be made with increasing frequency and based on the most current and valid data. However, respective tasks, e.g. PMA, require gathering explicit information from different parties, e.g. logistics, sales, and production planning hindered by intransparency, local optimisation, slow reactions, non-standardised databases, and high coordination effort. In the case of the use case partner Bosch, according to internal experts, this leads to more than 40% of the planning headcount regarding the current manual PMA processes is spent on acquiring data. To achieve high-quality results with reduced modelling effort, digital network twins (DT) are therefore increasingly being discussed (Table 1 – Requirement R4), the use of which was previously limited due to the irregularity of the planning tasks (Benfer, Peukert, and Lanza 2021).

To overcome the aforementioned problems, the present approach aims to support and accelerate manufacturing companies in making robust decisions regarding PMA taking into account business environment uncertainties and flexibilities as potential mitigation strategies. Therefore, information from scenarios generated by Monte–Carlo is processed using a model-based optimisation approach which considers product variants, GPN entities, transportation connections between manufacturing network entities, customers, periods, and production resources. Apart, the connection to various enterprise information systems and the continuous synchronisation of the optimisation model with these data sources enables the model to be used repeatedly with the latest information.

To successfully implement the solution approach, the remainder of the paper is structured as follows: Chapter 2 discusses relevant literature approaches in the field of robust decision-making in GPN. Chapter 3 introduces the methodology for a DT-based PMA in GPN which is validated against the use case of an automotive supplier in Chapter 4. Chapter 5 condenses the major insights and concludes with future research directions.

Literature review

To develop an approach that addresses the problems described above integratedly, various requirements are defined (R1–R4), against which the current state of the art is compared. Table 1 summarises the relevant approaches which are elaborated in detail in the following.

Research on incorporating uncertainty in GPN planning

When designing GPN structures and building allocation strategies, **considering uncertainty (R1)** of influencing factors is of crucial importance. However, the number of scenarios must allow an appropriate interpretation of the results (Lanza et al. 2019). Uncertain influencing factors that trigger changes within the GPN are referred to as change drivers (Wiendahl et al. 2007). Research on including uncertainty in network planning mostly use representative forecast models (Petropoulos and Siemsen 2023), parameter variations (Cuong et al. 2022) or stochastic models, e.g. Brownian Motion (Cuong et al. 2024) or Monte–Carlo simulation (Bihlmaier, Koberstein, and Obst 2009; Stähr, Englisch, and Lanza 2018) to consider change drivers in a variety of quantitative scenarios and representatively map a scenario funnel. Santoso et al. (2005) and Azaron, Venkatadri, and Doost (2021) develop stochastic scenarios using the Monte–Carlo simulation and reduce their number by applying a sample average approximation. To be applicable for the optimisation of order allocation, Buergin et al. (2019) reduce the number of scenarios through clustering. Khatami, Mahootchi, and Farahani (2015) include uncertainty scenarios, including the consideration of demand correlations by applying Cholesky's factorisation method. The number of initial scenarios is reduced by applying the K-means algorithm, where the optimal number of representative scenarios is determined by weighing computation time with the desired optimality gap. Baringo and Conejo (2013) build scenarios for investment decisions. First, they combine intervals of two uncertain parameters. Second, historical combinations of the uncertain parameters are clustered using K-means algorithm.

Approaches modelling flexibility in GPN

Numerous specific decision support models for PMA in GPN focus on one decision objective at a particular company. Comprehensive overviews are given e.g. by Lanza et al. (2019). The utilised models are often MILP models that focus on cost or net present value optimisation and may include additional objectives. However, **considering flexibilities in GPN modelling (R2)** to cope with uncertainties is necessary to broaden the solution space and find robust solutions. Originating from contributions focusing on defining flexibility in principle (e.g. Graves and Jordan 1995) and developing metrics for measuring flexibility (e.g. Sethi and Sethi 1990), authors like Bachlaus et al. (2008) incorporate flexibility in GPN modelling by considering two objective functions: one consists of several cost terms and the other objective function represents volume flexibility. In addition to an objective function cost component, factors such as delivery time, quality, and flexibility are also considered by Lanza and Moser (2014). Hochdörffer et al.

(2022) consider flexibility through a constraint and by adding a cost parameter in the objective function.

Approaches on robust decision-making in GPN

To cope with the increasing uncertainties mentioned above, *deriving robust decisions in GPN (R3)* is of major importance. Similarly to flexibility considerations, many approaches in this research area use single or multi-objective MILP to support PMA (Azaron, Venkatadri, and Doost 2021; Fattahi 2020; Khatami, Mahootchi, and Farahani 2015; Lanza and Moser 2014; Lotfi et al. 2021).

To model the decision-makers' willingness to take risks, many robust approaches incorporate risk aversion into their models. An entirely risk-averse model will consider equal scenario probabilities (Bertsimas and Sim 2003). As pointed out by Mulvey, Vanderbei, and Zenios (1995), modelling stochastic environments while only accounting for the worst-case outcome has been standardised in the literature despite them being exceptional cases of robust optimisation. Instead, approaches such as Govindan and Fattahi (2017) build on Bertsimas and Sim (2003) to investigate the deviation in model performance and outcome for such risk-averse robust objectives for all scenarios.

Approaches for DT of GPN

To overcome the hurdle of costly data acquisition and repeated modelling efforts also for medium- and long-term decisions, *representing GPN as DT (R4)* is a rather new but rapidly growing area of research. First approaches like Bergmann, Stelzer, and Strassburger (2011), automatically generate discrete event simulation models emphasising the need for precise simulation model initialisation in online simulations for dependable predictions. Their approach uses core manufacturing simulation data (CMSD) with necessary extensions and presents a prototype implementation. In the context of GPN, Gölzer et al. (2015) firstly introduced a big data approach to integrate ERP data into NoSQL databases. This approach aims to address the deficiencies of current methods and their practical implementation within real GPN, which often miss network-wide dependencies, by using Big Data techniques to enhance decision-making across the entire network. Ivanov and Dolgui (2021) introduce the concept of a digital supply chain twin, a real-time model representing network states. They investigate the implementation conditions of these twins in managing disruption risks within supply chains. Milde and Reinhart (2022) propose a concept to streamline simulation model development for order processing in GPN, focusing on enhancing efficiency by automating data preparation, model creation, and parameterisation. This approach, currently being developed for implementation in a German car manufacturer's engine production, aims to allow users to focus on executing and analysing simulation studies.

Synthesis and research gap

As depicted in Table 1 and elaborated in the previous sections, although several research approaches address some challenges in robust decision-making in GPN, none of the papers identified jointly fulfils all requirements for a holistic approach.

Regarding a combined consideration of uncertainties and flexibilities in the context of PMA, many approaches concentrate only on one individual aspect of both. On the one hand, in the context of uncertainty considerations, difficulties in deciding upon the number of scenarios in stochastic models and the need for effective methods to condense information from multiple scenarios into fewer ones for robust, cost-minimal decisions arise. On the other hand, in the context of flexibilities, insufficient attention is paid to solutions that simultaneously consider both, volume and product-mix flexibility integratedly. Considering the increasing variant complexity of products requiring special line features to be producible, identifying feasible product-mix allocations constitutes a complex task by itself. Further considering that lines may be upgraded by investments to let both, the capacity of the lines and volumes of thereby eligible variants at other plants to be recognised for volume flexibility represent important mitigation strategies for dealing with uncertainties. Hence, an integrated inclusion of representative scenarios and flexibility aspects is required for robust decision-making in the context of PMA. (Research Gap RG1 – Table 1 – green area).

In addition, the approaches identified in the context of robust decision-making in GPN are predominantly designed for single usage and neglect the digital representation of the models as well as the connection and continuous synchronisation with data sources. Hence, the research gap involves the challenge of integrating data from diverse sources within organisations to construct effective DT for GPN, emphasising the need for methodologies and strategies for data acquisition and integration in GPN decision-making contexts. (RG2 – Table 1 – red area). In contrast, approaches focusing on DT in GPN are rather conceptional and lack in practical applicability. However, integrating data from diverse sources in a real-world environment to create effective DT for GPN presents a significant challenge due to data sensitivity and diversity. Current research approaches therefore lack

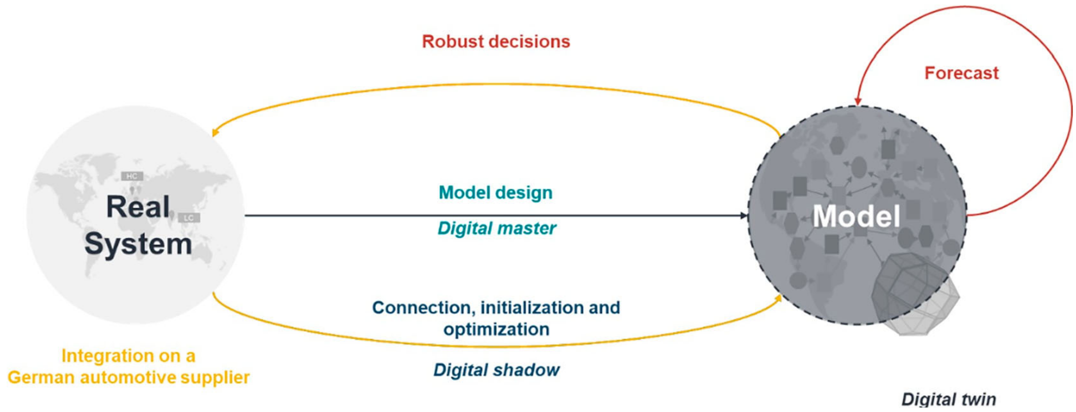


Figure 1. Robust planning of GPN (cf. Stark, Kind, and Neumeyer 2017).

in combining foundational decision-making frameworks and efficient structuring of simultaneous data acquisition from various systems, in one approach, which promises better decision-making in GPN (RG3 – Table 1 – yellow area).

Framework for robust planning of GPN

To overcome the shortcomings identified in the literature review, the present paper introduces a novel approach for finding robust decisions in PMA including flexibility and uncertainty aspects simultaneously. Therefore, a real system is first formalised during model design generating a digital master. Second, different production demand scenarios are forecasted, based on which robust decisions for the underlying real system are derived (RG1). All parameters, including the uncertainties, shall be gathered from a GPN data model to implement a DT (RG2) that guarantees the repetitive usability of the model for real-world use cases (RG3). The structure of the approach is depicted in Figure 1 and described in detail in the following.

Model design

In this section, the circumstances for the selection of the modelling techniques are described based on the specific needs of the company. Each site in the GPN of a particular product consists of several production lines. Each line has a nominal capacity boundary corresponding to regular working shifts. By utilising additional shifts and incurring corresponding costs, line capacity can be extended up to an absolute capacity boundary penalised by overutilisation costs per time unit. If planned shifts are not used, underutilisation applies. Product variants require specific technical production features. Each line has specific existing features and the possibility to purchase additional features through upgrades. The upgradeability differs for each line since not all technical specifications can be installed on every line. Customer orders may be produced on any line that possesses the necessary set of features. A production line may be shut down to save fixed costs. Similarly, new production lines may be constructed if utilisation exceeds capacity on existing lines. In addition to line features that are technically required, production can only take place if the customer has inspected the line for the fulfilment of quality requirements and issued a release. This release mechanism applies to entire production facilities as well, necessitating both line and site releases. Any release can be initiated by purchasing the release. Supplying production with relevant input materials or components may incur inbound logistics costs which accrue for orders that require pre-processing while considering site-specific pre-processing capacities. After production, finished goods are packaged and shipped either directly to the customer or to an intermediate warehouse, incurring outbound logistics costs. Both, in- and outbound logistics costs are defined per order and unit. Although seasonal demand may require intermediate inventories, due to the long-term nature and planning in half-year increments inventories and buffers are not considered. To incorporate volume and product-mix flexibility, sites possess outbound and inbound flexibility measures. Outbound flexibility is defined by the production volume that is anticipated to be produced at the site under consideration but could also be produced at another site. Inbound flexibility is defined by the production volume that the site under consideration would be able to take over from another site. For applicability in real GPN, the model must consider hard strategic constraints, like site contracts assuring a specific volume of produced products at a site. As these constraints are non-negotiable, techniques that find near-optimal solutions while considering consistently changing hard constraints were focused on. Optimisation models have a distinct advantage over heuristics in terms of flexibility. They possess the ability to automatically adapt to diverse decision variables and accommodate changing goals, constraints, and complexities prevalent in changing settings. The aspects considered allow for a linear mapping of the optimisation problem. Since this results in a complex combinatorial problem with a large number of possible discrete decisions, the model is built as a MILP.

Sets

Formally, the notation used denotes production facilities $s \in S$ composed of production lines $l \in L$ that receive and produce orders $o \in O$ over discrete time periods in a planning horizon $t \in T$ and are located in a triad $\gamma \in \Gamma$ (e.g. Asia-Pacific, Europe...). Note that a single order may span multiple periods, incurring different production volumes in each period. Production lines may possess or be upgraded to possess features $f \in F$. In the context of modelling inbound logistics costs, pre-processing facilities $\tilde{s} \in \tilde{S}$ and corresponding pre-processing orders $v \in V$ are considered necessary to fulfil orders. Every order entails an explicit set of 'sister orders' $\tilde{o} \in \tilde{O}_o$. The sister orders of an order are those produced for the same customer and product, sharing the same required customer release. The optimisation framework considers diverse demand scenarios denoted as $\omega \in \Omega$ emphasising joint optimisation across these scenarios.

Parameters

The parameters that capture the characteristics of the GPN are described in Appendices Table A2. Those parameters requiring a more detailed description are presented next. Individual realisations of the uncertain parameter of demand are represented for each order o in period t of scenario ω with volume η as parameter $\eta_{o,t,\omega}$. Scenario probability weights p'_ω are introduced to account for the likelihood of each demand scenario. Capacities are modelled as production time $k^{standard,existing}_{l,t}$ on line l in period t. The production cycle time parameter $\varrho_{o,l,t}$, i.e. the time required for producing one unit of a corresponding order on a line in a given period, adjusts the nominal cycle time $\zeta_{o,l,t}$ by the relative decrease through learning effects for later periods $\psi_{o,l,t}$ in 1:

$$\varrho_{o,l,t} = \zeta_{o,l,t} \cdot \prod_{t \in T} \left(1 - \frac{\psi_{o,l,t}}{100}\right) \tag{1}$$

Table 2. Variables.

	Meaning
Continuous variables	
$\delta^{overutilization}_{l,t,\omega}$	Degree to which utilised capacity exceeds available capacity
$\delta^{underutilization}_{l,t,\omega}$	Degree to which available capacity exceeds utilised capacity
$\upsilon_{o,l,t,\omega}$	Production duration of an order
$q_{o,l,t,\omega}$	Production volume of an order
$q^{flex}_{o,s_1,s_2,t,\omega}$	Indicates the flexible volume of producing an order on a line at a site s_1 which would also be producible at s_2
$\rho_{v,\tilde{s},s,t,\omega}$	Amount of pre-processing orders v that are transported from $\tilde{s}$ to s
$f^{in}_{s,t,\omega}$	Inbound flexibility of a site in a period
$f^{out}_{s,t,\omega}$	Outbound flexibility of a site in a period
Binary variables	
$e_{l,t,\omega}$	Indicates if a new line is opened in a certain period
$u^{existing}_{l,f,t,\omega}$	Indicates that a line possesses a particular feature
$u^{receiving}_{l,f,t,\omega}$	Indicates that a line receives a particular feature upgrade in a single period
$y^{line}_{o,l,\omega}$	Indicates if a customer release purchase is available for a line
$y^{facility}_{o,s,\omega}$	Indicates if a customer release purchase is available for a site
$y^{flex}_{o,\omega}$	Indicates if an order is flexible or not
$z_{l,t,\omega}$	Indicates if a line is active

Variables

The variables are summarised in Table 2 and explained more in detail in the following. The allocation of production volume $q_{o,l,t,\omega}$ in pieces of an order o to a line l in period t and scenario ω is introduced and transformed into $\upsilon_{o,l,t,\omega}$ as the corresponding utilised capacity measured in time units. Binary variables are introduced to model various investment decisions. For constructing new lines, the variable $e_{l,t,\omega}$ is used. Lines acquiring features f are denoted by $u^{receiving}_{l,f,t,\omega}$, and $z_{l,t,\omega}$ is introduced to indicate whether line l in period t and scenario ω is active for production. Furthermore, customer releases on lines $y^{line}_{o,l,\omega}$ and sites $y^{facility}_{o,s,\omega}$ can be acquired. Based on the defined minimum values for inbound and outbound flexibility invests are necessary to introduce the shipment of certain orders through warehouses, making them flex types $y^{flex}_{o,\omega}$. This means these orders can be fulfilled from different sites. The produced volume of these flex types is declared as the flexible volume $q^{flex}_{o,s_1,s_2,t,\omega}$, where s_1 denotes the nominal site and s_2 the available alternative. From the variable describing the produced volume $q^{flex}_{o,s_1,s_2,t,\omega}$, the inbound and outbound flexibility are calculated. This is described in the formulas 31-38.

Objective function

The MILP model entails a minimisation objective function consisting of individual cost components where c mentions the accordingly defined cost factor and p'_ω as weights for scenario probability. The model rewards delayed monetary flows by multiplying the incurred costs with the internal rate of return i_l^r.

$$min \sum_{\omega\in\Omega} p'_\omega \cdot \left(\sum_{t\in T} \frac{1}{(1+i_l^r)^t} \cdot \left(\sum_{o\in O} \sum_{l\in L} v_{o,l,t,\omega} \right.\right.$$

$$\cdot c_l^{variable} \cdot (1+i_l^{hc})^t \qquad (2)$$

$$+ \sum_{l\in L} \delta_{l,t,\omega}^{overutilization} \cdot c_l^{overutilization} \cdot (1+i_l^{hc})^t \qquad (3)$$

$$+ \sum_{l\in L} \delta_{l,t,\omega}^{underutilization} \cdot c_l^{underutilization} \cdot (1+i_l^{hc})^t \qquad (4)$$

$$+ \sum_{l\in L} z_{l,t,\omega} \cdot c_l^{fixed} \qquad (5)$$

$$+ \sum_{v\in V} \sum_{\tilde{s}\in\tilde{S}} \sum_{s\in S} \rho_{v,\tilde{s},s,t,\omega} \cdot c_{\tilde{s},s,v,t}^{inbound} \qquad (6)$$

$$+ \sum_{o\in O} \sum_{l\in L} q_{o,l,t,\omega} \cdot c_{o,l,t}^{outbound} \qquad (7)$$

$$+ \sum_{f\in F} \sum_{l\in L} u_{l,f,t,\omega}^{receiving} \cdot c_{l,f}^{feature,existing} \qquad (8)$$

$$\left.\left. \sum_{l\in L} e_{l,t,\omega} \cdot (c^{build} + c_l^{feature,new}) \right) \right) \qquad (9)$$

$$+ \sum_{o\in O} \sum_{l\in L} y_{o,l,\omega}^{line} \cdot c_{o,l}^{releaseline}$$

$$+ \sum_{o\in O} \sum_{s\in S} y_{o,s,\omega}^{facility} \cdot c_{o,s}^{releasefacility} \qquad (10)$$

$$\left. + \sum_{o\in O} y_{o,\omega}^{flex} \cdot c_o^{flexible} \right) \qquad (11)$$

In Equation (2), variable costs of lines are considered for the required production duration of orders and multiplied by the expected annual cost increase for production. This is mostly dependent on the wage increase parameter i_s^{hc}.

In Equation (3), overutilisation costs incurred from capacity utilisation exceeding the available standard capacity for each line in each period are summed.

In Equation (4), underutilisation costs incurred from available standard capacity exceeding the utilised capacity for each line in each period are summed.

For active lines, fixed costs specific to that line are incurred in 5. These costs are applied period-wise and are not dependent on the amount of production.

In Equation (6), inbound logistics costs are considered for the facilities s receiving semi-finished goods v that have been produced in a pre-processing site $\tilde{s}$. The inbound logistics costs per unit are multiplied periodically by the volume $\rho_{v,\tilde{s},s,t,\omega}$ of pre-processing units shipped.

In Equation (7), the production quantities are multiplied by the individual outbound logistics costs depending on the line.

Formula 8 involves accounting for upgrade costs incurred during the period when a feature upgrade is purchased for an existing line.

In Equation (9), build costs are incurred for building a new line, encompassing the expenses associated with installing features during the line's construction.

Formula 10 includes the summation of release costs for lines and facilities corresponding to specific orders.

Finally, in 11, flexibility costs associated with the number of flex types planned to be served from different sites concurrently are aggregated. These costs arise because orders served from two sites simultaneously require coordination through a joint warehouse, necessitating additional investment planning. Due to the high number of individual binary variables (dependent on o), a period-specific consideration is dispensed for releases and flex types in favour of shortening the calculation time. That also leads to no consideration of the internal cost rate.

Constraints

The model is subject to constraints, constituting the model's solution space. These are explained in the following subsection. Equation (12) guarantees that the production volume equals demand, ensuring demand is always fulfilled.

$$\sum_{l\in L} q_{o,l,t,\omega} = \eta_{o,t,\omega} \quad \forall o \in O, t \in T, \omega \in \Omega \qquad (12)$$

In Equation (13), the production duration for orders must match the production quantity multiplied by the cycle time adjusted by the equipment effectiveness of existing lines. Big-M is utilised to set this constraint inactive for new lines, where $e_{l,t,\omega} = 1$, since it ensures the right-hand side term to become negative, if the line was newly built in any period t. Note that $\theta_{l,t}^{existing}$ is the individual utility rate of the specific line.

$$v_{o,l,t,\omega} \geq q_{o,l,t,\omega} \cdot \frac{\varrho_{o,l,t}}{\theta_{l,t}^{existing}} - M \cdot \sum_{t\in T} e_{l,t,\omega}$$

$$\forall o \in O, l \in L, \omega \in \Omega \qquad (13)$$

In Equation (14), the production duration for orders is set to match the cycle time of production volumes adjusted by the equipment effectiveness of new lines. Big-M guarantees this constraint becomes active only when considering lines that are built in period t_1-t_2.

$$v_{o,l,t_1,\omega} \geq q_{o,l,t_1,\omega} \cdot \frac{\varrho_{o,l,t_1}}{\theta_{l,t_2}^{new}} - M \cdot (1 - e_{l,t_1-t_2,\omega})$$

$$\forall t_1, t_2 \in T, o \in O, l \in L, t_1 \geq t_2, \omega \in \Omega \qquad (14)$$

In Equation (15), the formulation ensures that production requires an active line, where the right-hand side becomes 0, if $z_{l,t,\omega} = 0$, correspondingly setting $q_{o,l,t,\omega}$ to 0.

$$q_{o,l,t,\omega} \leq z_{l,t,\omega} \cdot \eta_{o,t,\omega} \quad \forall o \in O, l \in L, t \in T, \omega \in \Omega \tag{15}$$

In Equation (16), lines remain inactive if the line was inactive in the preceding period and the line is not being opened in the current period. A line cannot be re-activated, since a shutdown often results in deconstruction to utilise the space for other production lines.

$$z_{l,t,\omega} \leq z_{l,t-1,\omega} + e_{l,t,\omega} \quad \forall l \in L, t \in T, t > 0, \omega \in \Omega \tag{16}$$

In Equation (17), the formulation ensures production is only possible if all required features for the order $\iota_{o,f}$ are available at the line $u^{existing}_{l,f,t,\omega}$.

$$q_{o,l,t,\omega} \cdot \iota_{o,f} \leq u^{existing}_{l,f,t,\omega} \cdot \eta_{o,t,\omega} \quad \forall o \in O, l \in L, t \in T, f \in F, \omega \in \Omega \tag{17}$$

In Equation (18), $u^{existing}_{l,f,t,\omega}$ can only become 1 if either the feature was initially available at a line $d_{l,f}$, the feature upgrade had been available in the previous period $u^{existing}_{l,f,t-1,\omega}$ or the feature upgrade was purchased in the current period $u^{receiving}_{l,f,t,\omega}$. For the initial period of $t = 0$, prior periods cannot be considered.

$$u^{existing}_{l,f,t,\omega} \leq \begin{cases} d_{l,f} + u^{existing}_{l,f,t-1,\omega} + u^{receiving}_{l,f,t,\omega}, & \text{if } t > 0 \\ d_{l,f} + u^{receiving}_{l,f,t,\omega}, & \text{otherwise} \end{cases} \quad \forall l \in L, f \in F, t \in T, \omega \in \Omega \tag{18}$$

In Equation (19), the formulation necessitates a release being available for production. Parameter μ enables or disables the consideration of sister orders in this constraint. Existing releases for an order and its sister orders are taken into consideration with $r^{line}_{o,l}$ and $r^{line}_{\tilde{o},l}$, respectively. If a release for the order is already available, the right-hand side of the inequation becomes 0, and no release can be purchased. If there is no release for the order available yet, a release is purchased if there is also no release for any sister order.

$$\left(y^{line}_{o,l,\omega} + \mu \cdot \sum_{\tilde{o} \in \tilde{O}_o} r^{line}_{\tilde{o},l} + y^{line}_{\tilde{o},l,\omega} \right) \cdot \eta_{o,t,\omega} \geq (1 - r^{line}_{o,l}) \cdot q_{o,l,t,\omega} \quad \forall o \in O, l \in L, t \in T, \omega \in \Omega \tag{19}$$

In Equation (20), the formulation ensures that the customer release for a line requires the customer release for the site. Again, releases for sister orders are considered with $y^{line}_{\tilde{o},l,\omega}$ and $y^{facility}_{\tilde{o},s,\omega}$. Whether a line belongs to a site is indicated by $b_{l,s}$. Parameter μ is applied to enable or disable redundant release purchasing for sister orders.

$$\left(y^{line}_{o,l,\omega} + r^{line}_{o,l} + \mu \sum_{\tilde{o} \in \tilde{O}_o} (r^{line}_{\tilde{o},l} + y^{line}_{\tilde{o},l,\omega}) \right) \cdot b_{l,s} \leq \left(y^{facility}_{o,s,\omega} + r^{facility}_{o,s} + \mu \sum_{\tilde{o} \in \tilde{O}_o} (r^{facility}_{\tilde{o},s} + y^{facility}_{\tilde{o},s,\omega}) \right) \cdot M \quad \forall o \in O, l \in L, s \in S, \omega \in \Omega \tag{20}$$

In Equation (21), the formulation ensures that capacities are available when allocating production volumes. Therefore, the sum of production quantities of a period multiplied by the respective cycle time must be less or equal to the corresponding available maximum line capacity in this period. When allocating production volumes to an existing line, the maximum capacity of this line $k^{maximum,existing}_{l,t_1}$, adjusted by the overall equipment effectiveness for existing lines $\theta^{existing}_{l,t_1}$, can not be exceeded. Once production volumes are allocated to a newly built line, θ^{new}_{l,t_2} must be employed to the maximum capacity of the new line $k^{maximum,new}_{l,t_2}$, since new lines exhibit much lower operational efficiency as existing lines. This means for any period t_1, where t_1 indicates the distance to the period in which the new line is opened, the capacity of this line adheres to the initial operational efficiency of new lines θ^{new}_{l,t_2} for that period t_2. The model is confronted with a dynamically shifting variable θ^{new}_{l,t_2} that is directly dependent on the manifestation of $e_{l,t,\omega}$.

$$\sum_{o \in O} q_{o,l,t_1,\omega} \cdot \varrho_{o,l,t_1} \leq \sum_{t_2 \in T} k^{max,new}_{l,t_2} \cdot \theta^{new}_{l,t_2} \cdot e_{l,t_1-t_2,\omega} + k^{max}_{l,t_1} \cdot \theta^{existing}_{l,t_1} \quad \forall l \in L, t_1 \in T, t_2 \in T, t_1 \geq t_2, \omega \in \Omega \tag{21}$$

Closely following the logic of Equation (21), where the capacity and equipment effectiveness of new and existing lines are considered separately, the required production duration of an order on a line is subtracted from the capacity of the line to determine the underutilisation $\delta^{underutilization}_{l,t_1,\omega}$ in Equation (22) and the overutilisation of a line $\delta^{overutilization}_{l,t_1,\omega}$ in Equation (23).

$$\delta^{underutilization}_{l,t_1,\omega} \geq k^{standard,existing}_{l,t_1} \cdot \theta^{existing}_{l,t_1} \cdot z_{l,t_1,\omega} + \sum_{t_2 \in T} k^{standard,new}_{l,t_2} \cdot \theta^{new}_{l,t_2} \cdot e_{l,t_1-t_2,\omega} - \sum_{o \in O} q_{o,l,t_1,\omega} \cdot \varrho_{o,l,t_1}$$

$$\forall l \in L, t_1 \in T, t_2 \in T, t_1 \geq t_2, \omega \in \Omega \quad (22)$$

$$\delta^{overutilization}_{l,t_1,\omega} \geq \sum_{o \in O} (q_{o,l,t_1,\omega} \cdot \varrho_{o,l,t_1}) - (k^{standard,existing}_{l,t_1} \cdot \theta^{existing}_{l,t_1} \cdot z_{l,t_1,\omega} + \sum_{t_2 \in T} k^{standard,new}_{l,t_2} \cdot \theta^{new}_{l,t_2} \cdot e_{l,t_1-t_2,\omega})$$

$$\forall l \in L, t_1 \in T, t_2 \in T, t_1 \geq t_2, \omega \in \Omega \quad (23)$$

In Equation (24), the formulation ensures that pre-process volumes equal the order volumes if a pre-process is required. $\chi_{o,v}$ is 1 if a pre-process v is required for an order o, and 0 otherwise.

$$\sum_{\tilde{s} \in \tilde{S}} \rho_{v,\tilde{s},s,t,\omega} = \sum_{o \in O} \sum_{l \in L} q_{o,l,t,\omega} \cdot \chi_{o,v} \cdot b_{l,s}$$

$$\forall t \in T, v \in V, s \in S, \omega \in \Omega \quad (24)$$

In Equation (25), it is defined that the required pre-process volume does not exceed the available production capacity of the pre-processing site.

$$\sum_{s \in S} \rho_{v,\tilde{s},s,t,\omega} \leq k^{preprocess}_{v,\tilde{s},t} \quad \forall v \in V, \tilde{s} \in \tilde{S}, t \in T, \omega \in \Omega \quad (25)$$

In Equation (26), the decision maker gets enabled to assign orders to specific facilities for all periods.

$$\sum_{l \in L} q_{o,l,t,\omega} \cdot b_{l,s} \leq \eta_{o,t,\omega} \cdot m_{o,s,t}$$

$$\forall o \in O, s \in S, t \in T, \omega \in \Omega \quad (26)$$

In Equation (27), fixating of orders and respective sister orders to specific facilities gets offered.

$$\sum_{\tilde{o} \in \tilde{O}} \sum_{l \in L} q_{\tilde{o},l,t,\omega} \cdot b_{l,s} + \sum_{l \in L} q_{o,l,t,\omega} \cdot b_{l,s} \geq \sum_{\tilde{o} \in \tilde{O}} x_{o,s,t} + x_{o,s,t}$$

$$\forall o \in O, s \in S, t \in T, \omega \in \Omega \quad (27)$$

In addition, Equations (28 and 29) implement that the model can ensure that a facility receives a minimum production volume and that a triad is served by a minimum share locally within the triad.

$$\sum_{o \in O} \sum_{l \in L} q_{o,l,t,\omega} \cdot b_{l,s} \geq w^{facility}_{s,t}$$

$$\forall o \in O, s \in S, t \in T, \omega \in \Omega \quad (28)$$

$$\sum_{o \in O} \sum_{l \in L} \sum_{s \in S} q_{o,l,t,\omega} \cdot b_{l,s} \cdot \kappa_{s,\gamma} \cdot \varsigma_{o,\gamma} \geq w^{triad}_{\gamma,t} \cdot \sum_{o \in O} \eta_{o,t,\omega} \cdot \varsigma_{o,\gamma}$$

$$\forall \gamma \in \Gamma, t \in T, \omega \in \Omega \quad (29)$$

In Equation (30), the formulation ensures that an order can only be declared as a flex type if releases for two different locations are existing or purchased.

$$2 \cdot y^{flex}_{o,\omega} \leq \sum_{s \in S} r^{facility}_{o,s} + \sum_{s \in S} y^{facility}_{o,s,\omega}$$

$$\forall o \in O, \omega \in \Omega \quad (30)$$

The proposed model combines volume and product-mix flexibility on the site level by implementing KPIs' for outbound and inbound flexibility. Three constraints determine the flexible production volume. Formula 31 specifies that the flexible production volume of an order must not be greater than the volume produced at that location. In Equations (32–34), the parameter M is used to specify that the volume produced is only deemed flexible if the corresponding order is declared as a flexible type and the corresponding releases are available.

$$q^{flex}_{o,s_1,s_2,t,\omega} \leq \sum_{l \in L} q_{o,l,t,\omega} \cdot b_{l,s_1}$$

$$\forall s_1, s_2 \in S, \text{t} \in T, o \in O, \omega \in \Omega \quad (31)$$

$$q^{flex}_{o,s_1,s_2,t,\omega} \geq \sum_{l \in L} q_{o,l,t,\omega} \cdot b_{l,s_1} - M \cdot (2 - (y^{facility}_{o,s_2,\omega} + r^{facility}_{o,s_2}) - y^{flex}_{o,\omega})$$

$$\forall s_1, s_2 \in S, t \in T, o \in O, \omega \in \Omega \quad (32)$$

$$q^{flex}_{o,s_1,s_2,t,\omega} \leq M \cdot y^{flex}_{o,\omega}$$

$$\forall s_1, s_2 \in S, \text{t} \in T, o \in O, \omega \in \Omega \quad (33)$$

$$q^{flex}_{o,s_1,s_2,t,\omega} \leq M \cdot (y^{facility}_{o,s_2,\omega} + r^{facility}_{o,s_2})$$

$$\forall s_1, s_2 \in S, \text{t} \in T, o \in O, \omega \in \Omega \quad (34)$$

In Equations (35) and (36), the inbound flexibility, the outbound flexibility, and the flexibility between locations are calculated. In Equations (37) and (38), the lower bound, which the planner can define, is applied for the existing in- and outbound flexibility.

$$f^{outbound}_{s_1,t,\omega} = \sum_{s_2 \in S} \sum_{o \in O} q^{flex}_{o,s_1,s_2,t,\omega} - \sum_{o \in O} q^{flex}_{o,s_1,s_1,t,\omega}$$

$$\forall s_1 \in S, t \in T, \omega \in \Omega \quad (35)$$

$$f^{inbound}_{s_1,t,\omega} = \sum_{s2 \in S} \sum_{o \in O} q^{flex}_{o,s_2,s_1,t,\omega} - \sum_{o \in O} q^{flex}_{o,s_1,s_1,t,\omega}$$

$$\forall s_1 \in S, t \in T, \omega \in \Omega \quad (36)$$

$$f^{inbound}_{s,t,\omega} \geq f^{mininbound}_{s} \cdot \sum_{o \in O} \sum_{l \in L} q_{o,l,t,\omega} \cdot b_{l,s}$$

$$\forall s \in S, t \in T \quad (37)$$

Table 3. Explanation of change drivers.

Change parameter	Indication
Reference	Defines the affected category and instance. Possible categories are order, customer, region, or variant, whereas instance defines the manifestation.
Probability (*P(C)*)	The occurrence probability of the change driver.
Influence (*I*)	Relative change caused by the change driver on occurrence.
Earliest period of entry (T_1)	Lower bound of the affected period range.
Latest ending period (T_2)	Upper bound of the affected period range.
Dependency	Describes how change drivers affect each other up to mutual exclusivity or condition. Therefore, keys have to be defined and set for orders which are dependent.

$$f^{outbound}_{s,t,\omega} \geq f^{minoutbound}_{s} \cdot \sum_{o \in O} \sum_{l \in L} q_{o,l,t,\omega} \cdot b_{l,s}$$

$$\forall s \in S, t \in T \tag{38}$$

Methodology to forecast representative production demand scenarios

To obtain a manageable number of scenarios with high significance, the following approach showed good results. The approach entails three core operations:

(1) Identify demand change drivers and their individual effects on demand volumes.
(2) Generate demand scenarios by applying a Monte–Carlo Simulation, which simulates the occurrences of change drivers.
(3) Reduce the number of scenarios with the K-Means algorithm to obtain a set of scenario clusters and their Euclidean centres as the final scenario set.

The results are published in Bruetzel et al. (2022).

Identifying change drivers

Scenario generation relies on the predictions of market researchers. For one, the automotive supplier forecasts the expected demand volumes for individual products. Additionally, individual market developments are predicted, and their expected effect on the current demand forecast for individual products or product groups is estimated. These market developments are referred to as demand change drivers. A change driver consists of the information listed in Table 3.

Monte–Carlo simulation

For generating a particular demand scenario $\tilde{\omega}$, the simulation process randomly iterates through the list of change drivers and generates random values within the defined bounds of the following three stochastic parameters for each change driver C. The realisation of the first stochastic parameter $X_{\tilde{\omega},C} \in \mathbb{R} | 0 \leq X_{\tilde{\omega},C} \leq 1$ determines whether the change driver occurs. If the stochastic parameter is within the probability space P_C of the change driver, $X_{\tilde{\omega},C} \leq P_C$, the change driver occurs. In this case, the two further stochastic parameters $Y_{\tilde{\omega},C}$ and $Z_{\omega,C}$, determine the period of entry and the period of end in which the change driver takes effect. The period of entry is defined by the realisation of Y, within bounds $Y \in [T_1, T_2]$. Y is then set as the new lower bound for the realisation of the stochastic parameter that determines the period of end Z, where $Z \in [Y, T_2]$. The demand volumes of the orders affected by the change driver are adjusted by the influence of the change driver I within the generated period bounds accordingly, where $I \in [-1, \infty]$. Mutual exclusivity or condition of a change driver is enabled through the dependency parameter, once one of these change drivers occurs. The process is repeated 100,000 times before the scenario reduction method is applied.

Scenario reduction

Finally, following the methodology proposed by Bruetzel et al. (2022), the large set of scenarios is reduced to a manageable set of representative scenarios $\boldsymbol{\Omega} : |\boldsymbol{\Omega}| = K$. Since the scenarios resulting from Monte–Carlo simulation are described by numerous (correlated) factors, e.g. volume per period, customer, and product variant groups, and are formalised by high-dimensional vectors, first, a principal component analysis (PCA) is applied to reduce scenario dimensionality while minimising the loss of information. With the reduced feature vectors of scenarios, K-means algorithm is applied, using random cluster centroids with adequate distancing to avoid local minima. The cluster assignment of each scenario vector is based on Euclidean distance. The algorithm optimises the cluster centroids by minimising the sum of squared Euclidean distances between all scenario vectors x_i and their corresponding assigned cluster centroid c_k. Once minimisation has been achieved, the nearest point x_i to a cluster centroid c_k constitutes the representative scenario since c_k may not be a scenario but just an empty point in the space. These points construct the set of representative scenarios $\boldsymbol{\Omega}$. The size of a cluster is defined by the number of points in the cluster $x_i \in k$. The relative size of clusters corresponds to the scenario probabilities p_ω.

Methodology for identifying robust decisions

The generalised framework follows the robust planning approach of Mulvey, Vanderbei, and Zenios (1995) based on stochastic programming, where variables are classified into recourse and non-recourse variables. Accordingly, an optimisation model of the following structure is considered,

$$\begin{array}{ll} \text{Minimise} & c^T x + d^T y, x \in R^{n_1}, y \in R^{n_2} \\ s.t. & Ax \geq b, \\ & Bx + Cy = e, \\ & x, y \geq 0 \end{array} \tag{39}$$

where $x \in R^{n_1}$ and $y \in R^{n_2}$ constitute the non-recourse and recourse variable vectors, respectively. The first constraint in Equation (39) represents those constraints unaffected by uncertainty, where A is a $m\ x\ n_1$ coefficient matrix and b represents a variable $m-$ vector. The second constraint represents all those constraints containing coefficients subject to uncertainty. This general optimisation model can be extended to include the individual realisations of the uncertain parameter, which are characterised by individual scenarios $\omega \in \Omega$ with occurrence probability p_ω, given $\sum_{\omega \in \Omega} p_\omega = 1$. Hence, the overall model minimises the expected value of the overall costs across all scenarios $\omega \in \Omega$ weighted by their associated probabilities p_ω, allowing decision-makers to set variables $e_{l,t,\omega}$, $u^{receiving}_{l,f,t,\omega}$, and $z_{l,t,\omega}$ to be non-recourse, i.e. fixed across the scenarios under consideration, for specific periods, constructing the sets Φ^e, $\Phi^{u^{receiving}}$, and Φ^z. The sets $\Phi^{y^{line}}$ and $\Phi^{y^{facility}}$ ensure consistency for the period-independent variables $y^{line}_{o,l,\omega}$ and $y^{facility}_{o,s,\omega}$. Variables deemed non-recourse in specific periods must be the same across all scenarios $\omega \in \Omega$. The variables $\delta^{overutilization}_{l,t,\omega}$, $\delta^{underutilization}_{l,t,\omega}$, $v_{o,l,t,\omega}$, $q_{o,l,t,\omega}$, $\rho_{v,\tilde{s},s,t,\omega}$ and $u^{existing}_{l,f,t,\omega}$ always remain recourse, following the assumption that the final allocation of volumes can be decided in the future on short notice, depending on the applying scenario.

Equations (40), (41), (42), (43), and (44) are constructed for the decision variables that may be deemed non-recourse. To ensure that each variable is non-recourse in the specific periods indicated by the decision maker, the respective sets of time periods for non-recourse variables $\Phi^{(\cdot)}$ get considered in each constraint. Equating the decision variables for all scenarios in the periods of $\Phi^{(\cdot)}$ guarantees them becoming non-recourse for the indicated periods.

$$e_{l,t,\omega_1} = e_{l,t,\omega_2} \quad \forall l \in L, \omega_1, \omega_2 \in \Omega, t \in T, t \in \Phi^e \tag{40}$$

$$u^{receiving}_{l,t,\omega_1} = u^{receiving}_{l,t,\omega_2} \quad \forall l \in L, \omega_1, \omega_2 \in \Omega, t \in T, t \in \Phi^{u^{receiving}} \tag{41}$$

$$y^{line}_{o,l,\omega_1} = y^{line}_{o,l,\omega_2} \quad \forall l \in L, \omega_1, \omega_2 \in \Omega, \Phi^{y^{line}} \neq \emptyset \tag{42}$$

$$y^{facility}_{o,s,\omega_1} = y^{facility}_{o,s,\omega_2} \quad \forall l \in L, \omega_1, \omega_2 \in \Omega, \Phi^{y^{facility}} \neq \emptyset \tag{43}$$

$$z_{l,t,\omega_1} = z_{l,t,\omega_2} \quad \forall l \in L, \omega_1, \omega_2 \in \Omega, t \in T, t \in \Phi^z \tag{44}$$

Second, the principles for modelling conservatism from Bertsimas and Sim (2003), who consider a risk-aversion parameter λ_i of the $i-$th constraint, get implemented in a simplified stochastic version to handle calculation time while at the same time enabling decision-makers to state the desired level of aversion by setting the risk-aversion parameter in range $\lambda \in [0, 1]$. Based on λ, adapted probability weights p'_ω, are defined in the following equation:

$$p'_\omega = \begin{cases} \left(\frac{1}{|\Omega|} - p_\omega\right) \cdot \lambda + p_\omega, & if\ \lambda > 0 \\ p_\omega, & otherwise \end{cases} \tag{45}$$

The risk-aversion parameter increases the weight of unlikely scenarios while decreasing the weight of likely scenarios.

Connection initialisation and optimisation

The following describes how the mentioned methods are transformed into a DT of a GPN. Stark, Kind, and Neumeyer (2017) structure the DT into a digital master and digital shadow, where the former is a generalised description of a group or class of entities, and the latter is a collection of all data related to a concrete entity throughout its lifecycle. When the digital master is logically linked to the digital shadow of a concrete instance, a DT is formed (see Figure 2). For further literature, the reader is referred to Jones et al. (2020).

The present approach for establishing a DT in GPN relies on a central database structured using the cross-divisional data model of GPN introduced by Benfer et al. (2023), which represents GPN and their characteristics in an object-oriented form. The generic architecture, consisting of four main object clusters (orders, products, production resources, and logistics), is devised and can be adapted to meet the specific requirements of an organisation. The database directly acquires data from various relevant data sources dispersed throughout an organisation including MES, ERP, CRM, and sometimes additional data sources for master data. These data may be complemented by additional manual inputs, e.g. the strategic premises, when optimisation runs are triggered by planners. The database comprises appropriate versioning that covers customisable deletion policies, current version flagging, and time validity features to ensure historical data integrity of the model in- and outputs. Therefore, each optimisation run relies on input data stored in

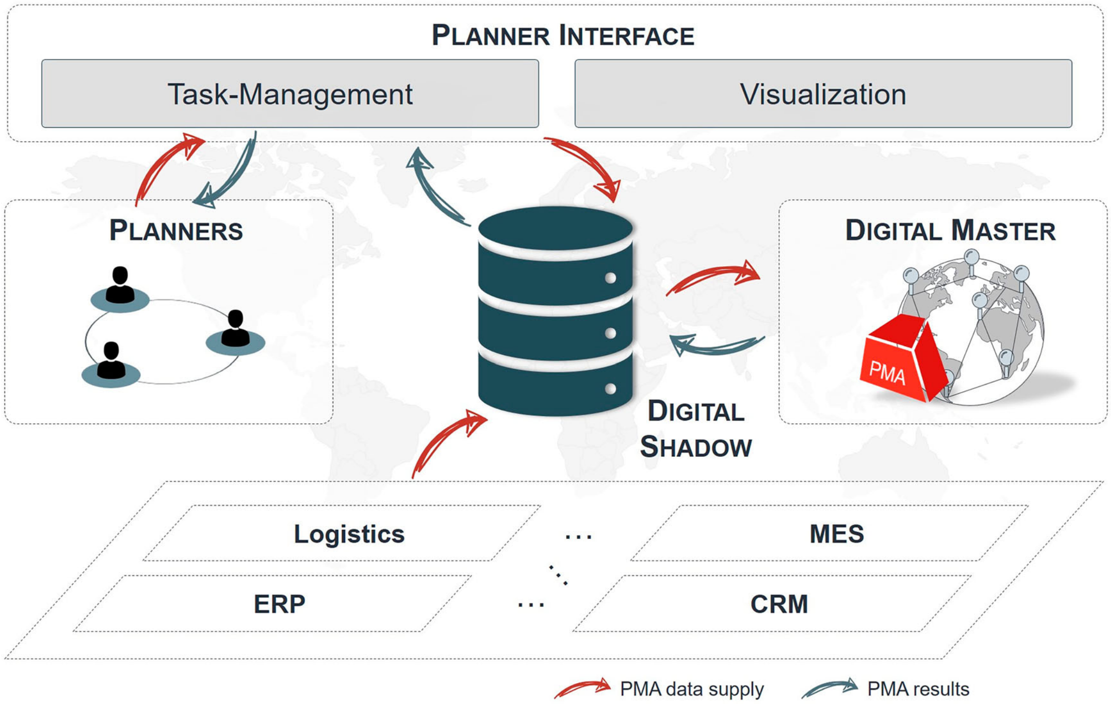


Figure 2. Components of the DT (cf. Stark, Kind, and Neumeyer 2017).

the database. Each run then is solved by the optimiser core. The corresponding optimisation results are written back to the respective run and directly may be visualised by Power BI so that planners can interactively gain an understanding of changes in the GPN decisions. Thus, linking the formalised optimisation core (Digital Master) to the central database fed by dispersed data sources (Digital Shadow) for each optmisation run creates a DT of the GPN.

Integration and quantification of results on an industrial GPN

The model is validated against the real use case of a Bosch Powertrain Solutions GPN, which is responsible for the final assembly, testing, and completion of combustion engine components. Given the anticipated changes in the car engine market, including a decline in demand for combustion engines shortly, the production system will require frequent modifications in the coming years to accommodate an increasing number of product variants while overall production volume decreases.

The product group in question comprises 1160 individual orders over 16 half-year periods, and its GPN comprises four production facilities with 15 lines in total located in Europe and Asia. Production is planned for up to 5–6 days a week in three 8-h shifts, depending on the site. The product is sold to 65 customers located in 21 different countries and based on the combination of 16 different features.

Evaluation of flexibility restriction without forecasting

Initially, the focus is on the quantification of the flexibility constraints 35–38 by applying inbound and outbound flexibility requirements, with $f_s^{mininbound}$ and $f_s^{minoutbound}$ of 50% compared to no constraints on flexibility. Figure 3 shows the associated results by depicting the relative/percentual change in the objective function value compared to optimisation without flexibility constraints for each cost component and cumulatively.

Overall costs increased by +11.90% compared to no flexibility requirements. As the model must ensure sufficient flexibility, it is forced to purchase more releases at several sites (+4.54%), make more product volumes producible on different lines by purchasing flex types (+4.01%), and upgrade the remaining lines in later periods (+0.31%). Furthermore, the lines in the high-cost location are consistently being used more intensively, as these lines are the most advanced in terms of existing features, thereby suffering higher variable costs (+3.9), but at the same time decreasing overutilisation costs in low-cost sites (−0.97%).

Forecasting of representative demand scenarios

In total, 29 change drivers are provided. An exemplary excerpt of change drivers is shown in Table 4. An

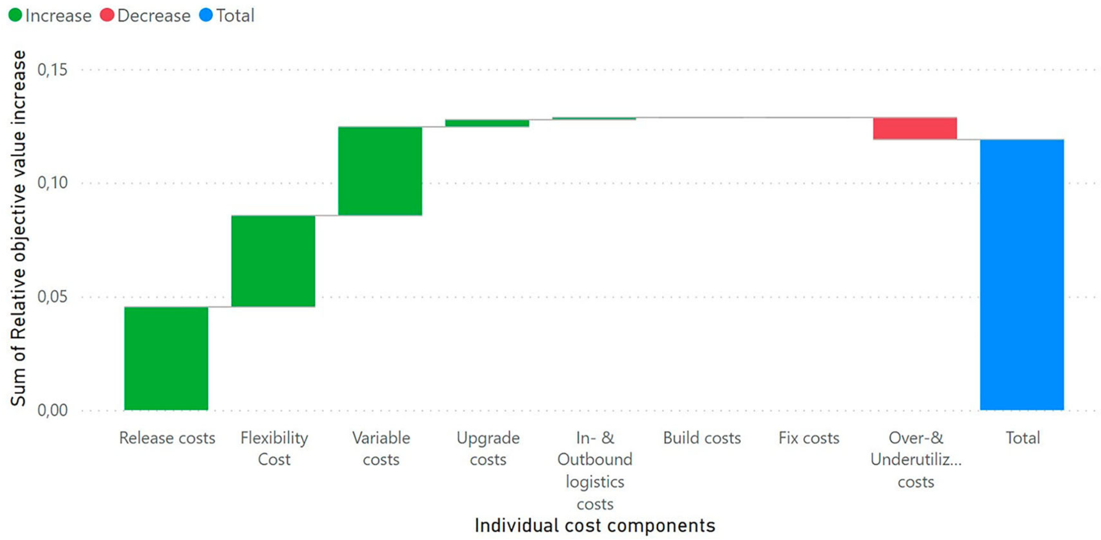


Figure 3. Relative change of the individual cost components by flexibility requirements.

Table 4. Examples of change drivers.

Change driver	Category	Instance	Probability ($P(C)$)	Influence (I)	Earliest period of entry (T_1)	Latest period of end (T_2)	Dependency
W3: New eFuel	Triad	EUR	0.1	0.2	7	16	–
W7: Quality problem	Part Number	1	0.05	−1	1	16	–

occurrence of W3 influences all products of the triad ‘EUR’, whereas W7 influences all products with the part number ‘1’.

With the data provided, a set of $K = 10$ representative demand scenarios is calculated (see Figure 4). The figure shows the cumulated periodic demand per half-year period. The line thickness indicates the probability weight p_ω of each scenario. The red baseline scenario represents the demand forecast without any change drivers.

Table 5 lists individual scenario probability weights and the cumulated demand volumes for all periods to provide comparability. On a more detailed level, these generated scenarios provide precise information on the order size of each order in the specific scenario $\eta_{o,t,\omega}$, enabling the robust modelling approach.

Application of the methodology to identify robust decisions

The transformation process of the originally deterministic model to a stochastic optimisation model that considers uncertainty must be weighed through quantitative comparison. The goal is to provide more robust decisions that collectively consider the produced demand scenarios. In this regard, the solution to the stochastic optimisation problem entails the costs incurred for integrated consideration of the demand scenarios by their respective probabilities.

To determine this cost disparity, a first experiment performs the most general means of comparison by uniformly setting $\Phi^{(\cdot)}$ to be non-recourse for all demand periods (robust model) and contrast the objective value with that of the deterministic model, where $\Phi^{(\cdot)}$ is generally recourse.

Considering the non-recourse nature of the decision variable $z_{l,t,\omega}$, the decision of which lines are active is made once for all scenarios, contrary to the deterministic model, where lines are deactivated in each scenario individually, as best fits. Cumulatively, the robust model shuts down lines over 52 periods exactly. In contrast, the deterministic model shuts down lines over 69.5 periods on average (25.2% increase), which is very similar to the 68 periods of the aforementioned flexibility approach. This results in more than triple the underutilisation costs in the robust optimisation model since capacity then exceeds utilisation in the low-volume scenarios.

Figure 5 shows an increase in underutilisation costs for the robust optimisation model. The relative cost increase when applying robust optimisation under these conditions amounts to 2.15% for 10 scenarios, which is considerable relative to potential savings due to the large-scale nature of this use case.

The costs of the robust and deterministic model are displayed on a periodical level in Figure 6 for each scenario. An increased parallelity in the non-recourse graph, especially for periods 8–9, can be observed. This directly

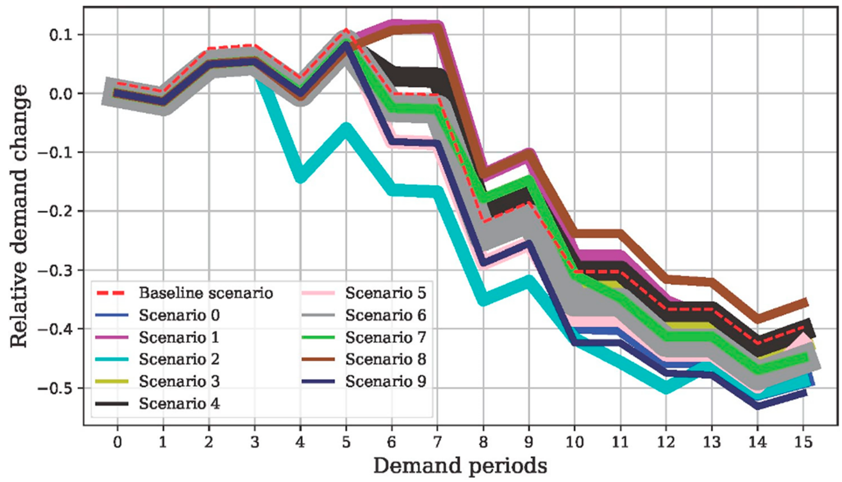


Figure 4. Diagramm for $K = 10$ representative demand scenarios.

Table 5. Scenario probabilities.

	Scenario (ω)									
	0	1	2	3	4	5	6	7	8	9
Probability weight (p_ω)	0.1266	0.0896	0.0789	0.1303	0.1314	0.09	0.1870	0.0642	0.0578	0.0437
Cumulated demand	0.9097	0.9795	0.8439	0.9332	0.9574	0.9022	0.9226	0.9378	1	0.8833

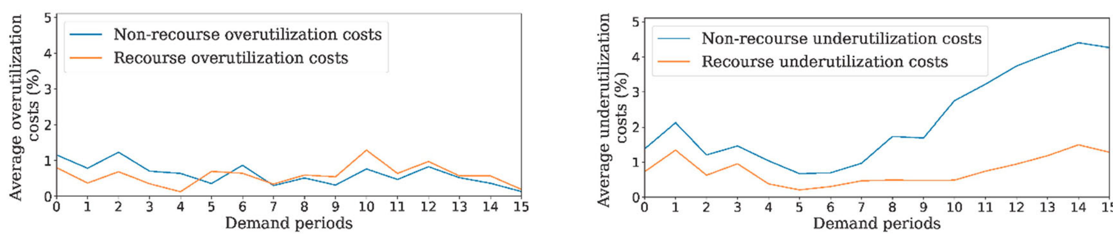


Figure 5. Periodical utilisation costs for the non-recourse and recourse decision of $z_{l,t,\omega}$.

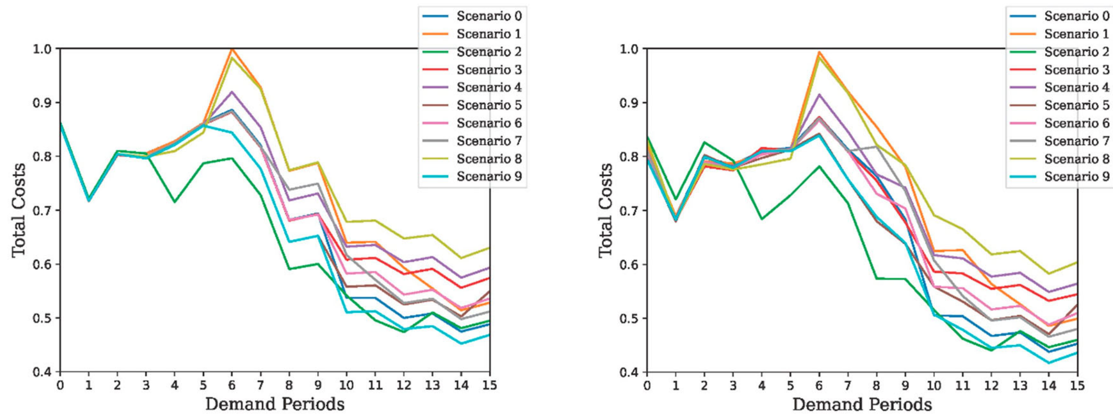
relates to the fact that the non-recourse decision variables are decided upon once for all scenarios.

Next, as summarised in Table 6 the effects of aversion are analysed by evaluating the performance of the robust model for different values of the risk-aversion parameter λ. For a thoroughly conservative model, where $\lambda = 1$, the overall costs slightly increase by 0.24% compared to the baseline scenario with unchanged scenario probabilities ($\lambda = 0$). To contrast this against the change in how demand is respected in the conservative model, a sum–product calculation (i.e. $\sum_{\omega\in\Omega} p'_\omega \cdot \sum_{o\in O}\sum_{t\in T}\eta_{o,t,\omega}$) for both $\lambda = 0$ and $\lambda = 1$ is performed, leading to a reduction of 0.08% of overall demand in the risk-averse scenario compared to the baseline scenario. This shows that the slight decrease in the overall demand is offset by the increasing probability of high-demand scenarios, such as scenarios 1 and 8.

The following analyses how the model performs for more exceptional situations since λ is specifically intended to mitigate the impact when facing more severe demand changes. Concerning existing production capacities, a fictive increase of the demand volume of high-volume, low-probability scenario 8 by 10% is performed to simulate overestimation. To enable an outcome comparison for this setting, the demand for low-volume, low-probability scenario 2 is decreased by 10% as underestimation.

The scenario probabilities for $\lambda = 0$ remain unchanged. The increase in demand affects the objective value far more (+1.21%) than the decrease (−0.46%). When setting $\lambda = 1$, the divergence of the objective value impact is strongly decreased. The objective value change for the demand increase (+1.53%) outweighs the objective value change for the demand decrease (−0.89%) far less than for $\lambda = 0$.

The final section of the results analysis discusses the impact different recourse settings of decision variables have on the overall cost of the GPN. The objective values for three additional fictive extreme recourse settings are listed in Table 7 to see strong effects and quantify the reaction of the optimisation each compared to the fully recourse setting set_0.



Periodic costs where $\Phi^{(\cdot)}$ is fully non-recourse

Periodic costs where $\Phi^{(\cdot)}$ is fully recourse

Figure 6. Periodic costs for 10 Scenarios.

Table 6. Impact of λ on the objective value for demand changes.

		$\lambda = 0$		$\lambda = 1$	
Changed scenario (ω)	Demand change	Relative sum–product of cumulated demand change	Relative objective value increase	Relative sum–product of cumulated demand change	Relative objective value increase
Baseline	Baseline	Baseline	Baseline	−0.08%	+0.24%
8	+10%	+0.65%	+1.21%	+1.1%	+1.53%
2	−10%	−0.72%	−0.46%	−0.83%	−0.89%

Table 7. Result comparison for different recourse decisions.

	Recourse indication for decision variables					Relative objective value
Setting	$e_{l,t,\omega}$	$u^{receiving}_{l,t,\omega}$	$y^{line}_{o,l,\omega}$	$y^{facility}_{o,s,\omega}$	$z_{l,t,\omega}$	change (%)
Fully recourse: set_0	1	1	1	1	1	0.00
Fully non-recourse: set_1	0	0	0	0	0	2.15
set_2	0	0	0	0	1	1.10
set_3	0	0	1	1	0	2.02
set_4	0	1	0	0	0	1.89

Deviating from the original model, set_2 only sets the line activity to be a recourse decision variable. In this case, the objective value increases by 1.1%. When only setting release purchases to be recourse decision variables (set_3), some reduction in the average release costs is observed, amounting to an objective value increase of 2.02%. Similarly, when setting the decision variable for line upgrade purchases to be recourse (set_4), high-volume scenarios no longer drive the model to place upgrade investments to ensure sufficiently available capacity on lines for all scenarios. This results in an objective value increase of 1.89%.

Industrial application of the methodology for identifying robust decisions

The concrete settings of which variables are not recourse have to be derived from the company strategy and depend on the speed of implementation of decisions. E.g. for a test at Bosch, decisions on investments in new features and the activity of existing ones were considered non-recourse for three years in this early time period. Releases were considered to be recourse. A performed experiment shows that reducing the reaction time of the three years by half to one and a half-years led to expected savings of 0.01% for all scenarios but 0.32% for the edge scenario with low volume. A last experiment compares how identified robust decisions perform against today's decisions from the deterministic model at the baseline scenario. Therefore, the decisions of the first three years are predetermined, such that these investments must be made, and no others are possible. Then, the model is applied deterministically 30 times on completely new, randomly drawn scenarios from the Monte–Carlo simulation, each by each. The result shows that the fixed decisions of the robust planning approach lead to expected relative objective decreases of 0.29% and outperform the baseline in 29 of 30 scenarios.

Conclusion and research perspectives

In summary, this study introduces a method to incorporate and quantify outcomes within an industrial Global Production Network (GPN) using typical demand scenarios. The approach was applied to Bosch's GPN as a case example, illustrating its implementation. The research underscores the influence of flexibility demands on costs and exhibits the process of creating representative demand scenarios. Moreover, it showcases the application of these scenarios in identifying robust decisions.

The study's findings reveal shifts in cost structure with the new approach, emphasising alterations in line utilisation and corresponding costs. Additionally, it was determined that when assuming all orders are met, robust decisions are more impacted by overestimates than underestimates of demand scenarios. It can be derived that edge scenarios benefit the most from shorter implementation cycles. Lastly, the presented robust planning approach leads to more robustness in scenarios that were not used for optimisation itself.

Apart from the economic advantages, on-site production is favoured due to the logistics costs and thus implicitly the emission costs. The approach therefore not only improves the cost structure, but also sustainability aspects. The method can be extended to other GPN, and different types of scenarios. Overall, the method provides a valuable tool for decision-makers to plan and optimise GPN under uncertain circumstances.

It is planned to examine the approach of daydreaming factories running optimisations if computational capacities exist (Nassehi et al. 2022). Analysing switching points of costs between different scenarios will help to understand bottlenecks in the GPN and solve them by broadening the solution space.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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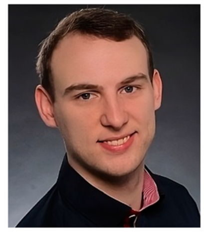

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Appendices

Table A1. Sets.

Set	Indication
Γ	Set of triads
Ω	Set of scenarios
$\Phi^{(\cdot)}$	Set of time periods in which decision variables are non-recourse
F	Set of possible line features
L	Set of production lines (existing and new)
O	Set of orders
$\tilde{O}_o$	Set of sister orders
S	Set of production facilities
$\tilde{S}$	Set of pre-processing facilities
T	Set of time periods (half-years)
V	Set of pre-processing orders

Table A2. Parameter.

Parameter	Meaning
$\chi_{o,v}$	Indicates the amount of pre-processing products required to produce a specific order.
$\eta_{o,t,\omega}$	Indicates the order size in units.
$\iota_{o,f}$	Indicates if a technical feature is required for an order.
μ	Enables the decision maker to decide if sister orders are to be respected when considering release purchases.
τ	Number of periods required to build a new line.
$\theta_{l,t}^{existing}$	Overall equipment effectiveness for existing lines. It is used to adjust the capacities by operational efficiency and includes local shift breaks and maintenance requirements.
$\theta_{l,t}^{new}$	Overall equipment effectiveness for new lines. New lines initially have efficiency drawbacks after construction.
$\varphi_{l,f}$	Indicates whether a line can be potentially upgraded by a feature.
$\psi_{o,l,t}$	Indicates the periodical relative decrease of production cycle time.
$\varsigma_{o,\gamma}$	Indicates the triad where the customer of an order is located.
$\kappa_{s,\gamma}$	Indicates if a site is in a triad.
$\zeta_{o,l,t}$	Indicates the nominal cycle time for producing one unit of an order.
$\varrho_{o,l,t}$	Indicates the cycle time for producing one unit of an order.
$a_{o,l}^{line}$	Indicates if an order is initially assigned to a line in period 0.
$a_{o,s}^{facility}$	Indicates if an order is initially assigned to a site in period 0.
$b_{l,s}$	Indicates if a line belongs to a site.
c^{build}	Basic Costs for building a new line.
$c_{l,f}^{feature,existing}$	Costs for upgrading an existing line with a feature.
$c_{l}^{feature,new}$	Costs for having a feature built together with building a new line.
c_{l}^{fixed}	Fixed costs of a line.
$c_{v,s,\tilde{s}}^{inbound}$	Inbound logistics costs per unit.
$c_{o,l,t,\omega}^{outbound}$	Outbound logistics costs per unit per scenario.
$c_{l}^{overutilization}$	Costs for overutilisation of a line. These costs are incurred once the standard capacity of a line is exceeded.
$c_{o,l}^{releaseline}$	Costs for purchasing a customer release for a line.
$c_{o,s}^{releasefacility}$	Costs for purchasing a customer release for a site.
$c_{l}^{underutilization}$	Costs for underutilisation of a line. These costs are incurred once the standard capacity of a line is not reached.
$c_{l}^{variable}$	Variable costs for lines.
$c_{o}^{flexible}$	Costs for purchasing a order to be flexible
$d_{l,f}$	Indicates if a feature is initially available at a line.
$f_{s}^{mininbound}$	Minimum required inbound flexibility at a site
$f_{s}^{minoutbound}$	Minimum required outbound flexibility at a site
i_{l}^{hc}	Parameter for the periodic percentage cost increase of headcount
i_{l}^{invest}	Parameter for the periodic percentage cost increase of investments (internal interest rate) per line
$k_{l,t}^{maximum,exisiting}$	Maximum capacity of an existing line.
$k_{l,t}^{standard,existing}$	Standard capacity of an existing line.
$k_{l,t}^{maximum,new}$	Maximum capacity of a new line.
$k_{l,t}^{standard,new}$	Standard capacity of a new line.
$k_{v,\tilde{s},t}^{preprocess}$	Capacity of the site that manufactures the pre-processing products.
M	Large number used to influence the sing of a term
$m_{o,s,t}$	Indicates whether an order should be fixated to a site during specific periods.
$r_{o,l}^{line}$	Indicates whether a customer release is available for a line.
$r_{o,s}^{facility}$	Indicates whether a customer release is available for a site.
$w_{s,t}^{facility}$	Indicates the requirement for a minimum share of total production volume at a site.
$w_{\gamma,t}^{triad}$	Indicates the requirement for a minimum share of total production volume in a triad.
$x_{o,s,t}$	Defines a minimum volume share of production per order to be fixed to a site.