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Regionalized implementation strategy of smart automation within assembly systems in China

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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 soll im Rahmen dieser Schriftenreihe über aktuelle Forschungsergebnisse des Instituts für Produktionstechnik (wbk) am Karlsruher Institut für Technologie (KIT) berichtet werden. Unsere Forschungsarbeiten beschäftigen sich sowohl mit der Leistungssteigerung von Fertigungsverfahren und zugehörigen Werkzeugmaschinen- und Handhabungstechnologien als auch mit der ganzheitlichen Betrachtung und Optimierung des gesamten Produktionssystems. 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

Vorwort des Verfassers

This dissertation is the result of my work as a research associate at the wbk Institute of Production Science of the Karlsruhe Institute of Technology (KIT). I would like to thank the entire board of management for its professional and personal support.

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Karlsruhe, 10.02.2021

Shun Yang

Institut für Produktionstechnik

Karlsruher Institut für Technologie

Kurzfassung

Produzierende Unternehmen in aufstrebenden Nationen wie China, sind bestrebt, die Produktivität der Produktion durch eine Verbesserung der Lean Produktion mit disruptiven Technologien zu erreichen. Smart Automation ist dabei eine vielversprechende Lösung, allerdings können Unternehmen aufgrund von mangelnden Ressourcen oft nicht alle Smart Automation Technologien gleichzeitig implementieren. Ebenso beeinflusst eine Vielzahl an Einflussfaktoren, wie z.B. Standortfaktoren. Dementsprechend herausfordernd ist die Auswahl und Priorisierung von Smart Automation Technologien in Form von Einführungsstrategien für produzierende Unternehmen.

Der Stand der Forschung untersucht nur unzureichend die Analyse der Interdependenzen zwischen Standortfaktoren, Smart Automation Technologien und Key Performance Indikatoren (KPIs). Darüber hinaus mangelt es an einer Methode zur Ableitung der Einführungsstrategie von Smart Automation Technologien unter Berücksichtigung dieser Interdependenzen.

Entsprechend trägt diese Arbeit dazu bei, eine regionalisierte Einführungsstrategie von Smart Automation Technologien in Montagesystemen zu ermöglichen. Zunächst werden die Standortfaktoren, Smart Automation Technologien und KPIs identifiziert. In einem zweiten Schritt werden, mit Hilfe von qualitativen und quantitativen Analysen, die Interdependenzen bestimmt. Anschließend werden diese Interdependenzen auf ein Montagesystem mittels hybrider Modellierung und Simulation übertragen. Im vierten Schritt wird eine regionalisierte Einführungsstrategie durch eine Optimierung und eine Monte-Carlo-Simulation abgeleitet. Die Methodik wurde im Rahmen des deutsch-chinesischen Forschungsprojekts I4TP entwickelt, das vom Bundesministerium für Bildung und Forschung (BMBF) unterstützt wird. Die Validierung wurde erfolgreich mit einem produzierenden Unternehmen in Beijing durchgeführt.

Die entwickelte Methodik stellt einen neuartigen Ansatz zur Entscheidungsunterstützung bei der Entwicklung einer regionalisierten Einführungsstrategie für Smart Automation Technologien in Montagesystemen dar. Dadurch sind produzierende Unternehmen in der Lage, individuelle Einführungsstrategien für disruptive Technologien auf Basis wissenschaftlicher und rationaler Analysen effektiv abzuleiten.

Contents

List of Abbreviations and Symbols

Abbreviations	Description
ABS	Agent Based Simulation
AGV	Automated Guided Vehicle
AI	Artificial Intelligence
AM	Agile Manufacturing
AMSs	Advanced Manufacturing Systems
AMT	Advanced Manufacturing Technology
AR	Augmented Reality
AS	Available System
AS40	Assembly System 4.0
ATA	Automatic Torque Adjustment
BT	Break Time
CAFS	Chinese Academy of Fiscal Sciences
CIM	Computer-Integrated Manufacturing
CMfg	Cloud Manufacturing
Conc. eng.	Concurrent Engineering
CPS	Cyber-Physical Systems
CPPS	Cyber-Physical Production Systems
CS	Computer Science
Csourcing	Crowd-sourcing
C/O	Changeover Time
C/T	Cycle Time
DES	Discrete Event Simulation
DSFM	Digital Shopfloor Management
EE	Extended Enterprises
EPEI	Every Part Every Interval
ERP	Enterprise Resource Planning

ES	Effectiveness System
FMS	Flexible Manufacturing System
FPY	First Pass Yield
GAMI	Global Advanced Manufacturing Institute
GDP	Gross Domestic Product
GQC	Good Quantity Counted
HMI	Human Machine Interaction
HMS	Holonic Manufacturing System
I4.0	Industry 4.0
ICT	Information and Communication Technologies
IMF	International Monetary Fund
INS	Intelligent Screwdriver
IoT	Internet of Things
JIT	Just in Time
KPIs	Key Performance Indicators
LP	Lean Production
LM	Lean Management
LoFa	Location Factors
MAS	Multi-agent System
MES	Manufacturing Execution System
ML	Machine Learning
MS	Manufacturing Systems
MTBF	Mean Time Between Failure
MTTF	Mean Time To Failure
MTTR	Mean Time To Repair
MWIP	Mean Work In Process
NE	Number Of Employees
NM	Networked Manufacturing

NOWIP	Number Observations of Work In Process
ODT	Other Down Time
OEE	Overall Equipment Effectiveness
OLE	Overall Labor Effectiveness
PBL	Pick By Light
PBT	Planned Busy Time
PDT	Planned Down Time
PLM	Product Lifecycle Management
PMT	Preventive Maintenance Time
PN	Production Networks
POT	Planned Operation Time
PQ	Produced Quantity
PROD	Productivity
PSS	Product Service System
QCD	Quality, Cost And Delivery
QR	Quality Rate
QR Code	Quick Response Code
QRCS	Quality Ratio Counted System
RFID	Radio Frequency Identification
ROI	Return On Investment
SCM	Supply Chain Management
SCQ	Scrap Quantity
SD	System Dynamics
SG	Smart Gloves
SmAu	Smart Automation
SPSS	Statistical Package For The Social Science
TOAA	Time For Other Administrative Actions
TPS	Toyota Production Systems

VDI	Association Of German Engineers
VDMA	Association Of German Mechanical Engineering Industry
VR	Virtual Reality
VSM	Value Stream Mapping
VUCA	Volatility, Uncertainty, Complexity And Ambiguity
V&V	Verification & Validation
WCR	Workplace Carrier With RFID Tags
WIP	Work In Process
WN	Wireless Nutrunner
ZVEI	German Electrical And Electronic Manufacturers´ Association

Symbols	Description	Unit
$a_{i,j}(n)$	Individual metrics between location factors and Smart Automation technologies, where i represents for row number, j for column number and n for each expert	-
A_i	Output state	-
$A_{i,j}$	Arithmetic average of corresponding values from expert interviews for location factors	-
AVA	KPI indicator – availability	-
$b_{i,j}(n)$	Individual metrics among different smart automation technologies, where i represents for row number, j for column number and n for each expert	-
$B_{i,j}$	Arithmetic average of corresponding values from expert interviews for Smart Automation	-
c_i	Value of key figure	-
c_i^{min}	Minimum value of key figure	-
c_i^{max}	Maximum value of key figure	-
Cof_n^{n-1}	mutual incentive coefficients between $Tech_n$ and $Tech_{n-1}$	-
$Const_{invest}$	Constraint value of investment cost	-
$Const_{days}$	Constraint value of implementation days	-
$Cost$	KPI indicator – cost	-
$Days_T$	Total implementation days of technologies	-
DEL	KPI indicator – delivery	-
Δu	Varying conditions	-
D_n	Implementation days of individual technology	-
γ_i	Normalization of key figure	-
i	Multi-purpose index used in several contexts, if just a single index is required	-
$invest_n$	Investment cost of individual technology	-
$Invest_T$	Total investment of technologies	-
j	Multi-purpose index used in several contexts, if just a single index is required	-
k	Total amount of technology available	-
$L(x,u)$	Stable target function value	-

n_{NE}	Number of employees	-
n_{GQC}	Number of produced good parts by first run	-
n_{SCQ}	Number of defect parts	-
n_{WIP}	Number of Work in Process	-
ω_i	Weight of KPIs	-
QUA	KPI indicator – quality	-
S_{Ai}	Score of corresponding aspect	-
S_i	Final score of each item	-
S_{Ii}	Score gained of each item in its aspect	-
t_{AWUBT}	Actual work unit busy time	TU
t_{CT}	Cycle time	TU
t_{CToB}	Cycle time of bottleneck	TU
$Tech_i$	Technology i	-
t_i	Number of days already spent for the technology i	-
T_i	Total days the technology needs to be entirely implemented	-
t_{LDT}	Logistic delay time	TU
t_{ODT}	Other down time	TU
t_{PBT}	Planned busy time	TU
u	Influencing factors	-
v_{DF}	Defect rate	%
v_{FPY}	Value of First Pass Yield	%
v_{PROD}	Value of productivity	-
v_{UT}	Machine availability	%
x	Possible solution	-
y	Implementation effect level	-
$z_{i,j}$	Number of individual metrics	-

1 Introduction

Digitalization could create an estimated 100 trillion dollars in value over the next decade[1]. Industry 4.0 and the underlying digital transformation is progressing exponentially (Ghobakhloo 2020). Meanwhile, Industry 4.0 is realizing the extended lean enterprise (Davies & Coole et al. 2017). However, adequate implementation of Industry 4.0 technologies can be a challenge for both industry representatives and countries (Da Silva & Kovaleski et al. 2020). To adopt the concept of Industry 4.0, one of the critical barriers identified is the lack of a theoretical model or procedure that best directs or assists managers (Schröder 2016; Orzes & Rauch et al. 2018). Thus, the success of Industry 4.0 will depend upon a series of well-planned and strategically executed projects (Sony & Naik 2020). Thus far, research has not dealt with the interplay between location factors such as humans, organization and technology (Veile & Kiel et al. 2019; Schuh & Anderl et al. 2017). Therefore, the regionalized implementation strategy of disruptive technologies must be scientifically investigated to understand influence factors, navigate transformation process and ensure added value for the production sector.

1.1 Background and Motivation

The Lean production paradigm has become the major approach to create highly efficient processes in industry since the early 1990s (Dombrowski & Schulze et al. 2009; Dombrowski & Schmidt et al. 2008; Peter 2009; Womack & Jones et al. 1990). After the end of the Computer Integrated Manufacturing (CIM) era, which was doomed to fail due to its unmanageable complexity of the required automation technology and its shortcomings in adapting to dynamic changes in a production system (Yu & Xu et al. 2015), the Lean approach became successful because of its high effectiveness by reducing complexity and avoiding non-value-creating processes (Kolberg & Zühlke 2015). Its simplicity and up to 25% higher productivity are important reasons why Lean production has become status quo of production systems (Dickmann 2007). Although Lean production supports a higher variety of products, its fixed sequence of production and fixed cycle times are not suitable for individual single-item production. Thus, the suitability of classical Lean methods for future shorter product life cycles and individual single-item production is limited (Kolberg & Zühlke 2015).

Today, the ability of a production system to produce a special product is changing due to digital evolution (Reinhart & Krug et al. 2010). Increasing networking and the ubiqui-

[1]WEF (2018), Digital Transformation Initiative, Executive Summary, May 2018, http://reports.weforum.org [14.10.2020]

tous availability of data and services offer entirely new and promising prospects for industrial automation. Amongst others, there is the vision of adaptive, self-configuring, partially self-organizing and flexible production facilities. This would revolutionize production, offering enhancement to Lean production through shorter set-up times and optimized use of energy and resources, reducing waste and workload and improved deficit and abnormality detection (Rossini & Costa et al. 2019). This vision, presented within the framework of the German federal government's "Industrie 4.0" future project, is referred to as Cyber-Physical Production Systems (CPPS) (Bettenhausen & Kowalewski 2013). Similar initiatives run in different countries under different names, as, for instance "Made in China 2025" in China[1].

CPPS is defined as the application of Cyber-Physical Systems (CPS) in industrial production (Posada & Toro et al. 2015; Monostori & Kádár et al. 2016). The term CPS refers to a technical system that has at least one of the three following features: extensive utilization of sensor technologies for analytics, connected network of multiple technical components with extensive data exchange, and autonomous operation of subsystems (Manzei & Schleupner et al. 2017). According to the common understanding, the purpose of the application of CPS is to interact with people in CPPS to support them with production tasks (Manzei & Schleupner et al. 2017). Since the CPPS is quite a broad concept, this thesis is focused on smart automation technologies in the framework of CPPS.

Smart automation describes an intelligent automatic production process that is characterized by the active support of intelligent products and technologies. By means of a high degree of digitalization, the potentials of information technology are to be utilized by automated monitoring of the production process, which allows higher flexibility and simultaneously higher productivity (Yang & Boev et al. 2018; Yang & Schrage et al. 2019). Smart automation technologies can be of very different nature, including hardware components, such as driverless transport vehicles or RFID chips, as well as software components, such as digital shopfloor management or digital work instructions. Thus, such smart automation concepts provide the potential to enhance existing Lean Production Systems by capturing, storing, distributing, managing, and analyzing the information. In order to exploit this potential, however, today´s manufacturers face the challenge of how to effectively integrate smart automation concepts into their current Lean Production Systems. In particular, this involves identifying the most suitable smart automation for their specific purposes.

[1]The State Council of People's Republic of China, Made in China 2025, http://english.www.gov.cn/2016special/madeinchina2025/ [19.10.2020]

In general, difficulties occur mainly due to differing perceptions of the principal nature of these new concepts, as well as the complexity of related topics (Monostori 2015; Schumacher & Erol et al. 2016). Additionally, the intended improvements of using a combination of the smart automation concepts has not yet been quantitatively analyzed for superior performance characteristics with regard to relevant Key Performance Indicators (KPIs), such as product throughput times, production costs, and quality rates. Also, which specific sequential combinations of smart automation concepts companies could achieve optimal performance is often a complex decision. Thus, the corresponding decisions regarding the integration of smart automation concepts in Lean Production Systems cannot be effectively made (Yang & Schrage et al. 2019; Liebrecht 2020).

Moreover, by considering the global environment, the role of location factors is very important for ideal preparation of production improvements (Ketokivi & Turkulainen et al. 2017). While the company faces challenges about the variety of improvement possibilities and limited resources regarding the smart automation application, location factors can support companies in identifying the most valuable improvement areas by considering their individual factors, such as markets and market development, cost, logistics, cultural factors, political and governmental factors, legal factors, risk through dynamics and uncertainties, among others (Feldmann & Olhager 2013). Without consideration of related location factors, the key fields of smart automation application cannot be appropriately identified. Therefore, it is necessary to investigate a set of location factors and its influence on smart automation.

With reference to the initial situation, the identification of suitable strategies for implementing Smart Automation technologies for enhancing Lean production by considering location factors is an increasingly important challenge in research and industrial practice.

1.2 Scope of the Research

The scope of the work is limited to assembly systems in China. Firstly, assembly is a very important process in manufacturing. Assembly of manufactured goods accounts for over 50% of total production time and 20% of total production cost. In the automotive industry, 20%-70% of the direct labor costs are spent on assembly. These statistics indicate the relative importance of assembly and point to the potential savings to be achieved by improving assembly technology and systems (Eimaraghy & Eimaraghy

2016). Therefore, the assembly system is one of the most important parts in a production system and needs to be designed and operated to handle a wide variety of products. Thus, it is meaningful to focus on this field.

Secondly, in terms of global production, China as an emerging country has shown much higher growth in its manufacturing industry than ever before, owing not only to its traditional low-cost value proposition, but also its focus and development of innovation infrastructure to cement the role of advanced technologies in its manufacturing future. According to the Global Competitiveness Report 2019 (WEF 2019[1]), China ranks 28th overall, unchanged from the previous edition (see Figure 1-1). Its score increased by 1.3 points, driven by a significant boost in Information and Communication Technologies (ICT) adoption (78.5, 18th). Despite these encouraging signs, however, growth has been steadily declining in recent years. While Gross Domestic Product (GDP) grew by 10.61% in 2010, growth in 2017 was only 6.86% (IMF 2018[2]). The manufacturing companies are also facing great challenges such as increasing labor costs and high material costs. They are dealing with relatively low productivity and flexibility on the one hand, and growing customer demand regarding delivery time, product varieties and product quality on the other hand. Instead of continuing to serve the global demand for low-cost products as the "work-bench of the world", the industry is increasingly focusing on sustainable, domestic market-oriented, socially balanced and innovation-driven development. In order to achieve this without compromising growth, the productivity of domestic production facilities must be increased significantly (Schüller 2015).

[1]World Economic Forum, The Global Competitiveness Report 2019, http://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2019.pdf [19.10.2020]

[2]International Monetary Fund, https://www.imf.org/external/datamapper/datasets [19.10.2020]

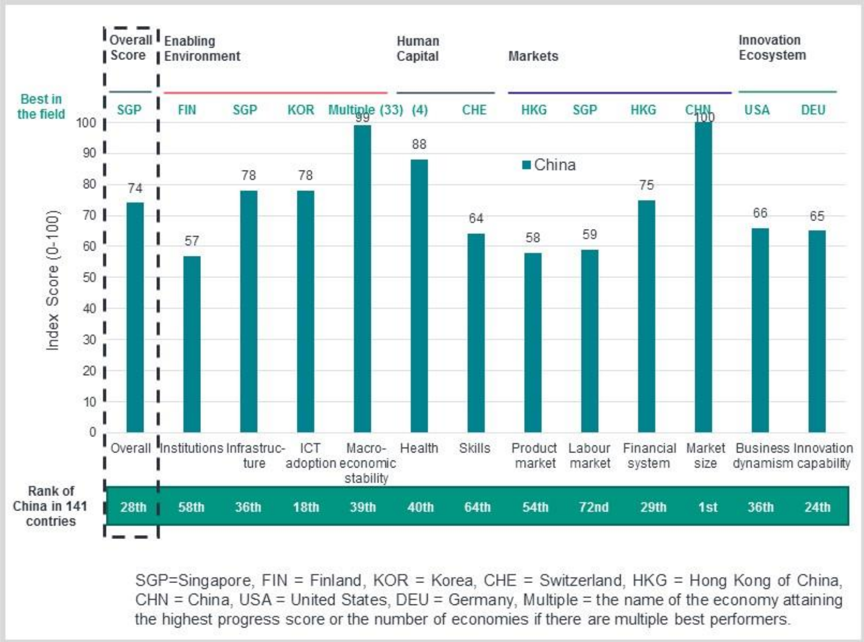


Figure 1-1: Global Competitiveness of China 2019 (WEF 2019)

Meanwhile, a strategic plan was presented in China in 2015 with an emphasis on a shift in Chinas manufacturing economy from quantity to quality. Operation costs, lead time and the defect rate in local factories are targeted to decrease by 50% by 2025[1] (see Table 1-1). To achieve this increase in productivity, the introduction of intelligent production must be stepped up. According to a study, over 70% of Chinese industrial companies are still in the observation and analysis phase, or have not even considered it yet, and insufficient know-how is one of the top obstacles[2].

Table 1-1: Strategic goals of manufacturing in 2020 and 2025[1]

Category	Indicator	2013	2015	2020	2025
Innovation Capability	Internal R&D cost as a percentage of operating revenue of manufacturing firms (%)	0.88	0.95	1.26	1.68
	Invention patents per billion RMB of operating revenue (#)	0.36	0.44	0.70	1.10
Quality and Value	Manufacturing quality competitiveness (index)	83.1	83.5	84.5	85.5

[1]Kennedy, S. (2015), "Made in China 2025" Center for Strategic and International Studies. https://www.csis.org/analysis/made-china-2025 [09.04.2020]

[2]Staufen AG (2015), "China - Industrie 4.0 Index 2015". https://www.staufen.ag [13.07.2020].

	Manufacturing value-added rate (% increase over 2015)	-	-	2	4
	Average manufacturing labor productivity growth during the 5-year Plan (%)	-	-	7.5	6.5
Integration of Informa-tization and Industriali-zation	Broadband penetration (%)	37	50	70	82
	Digital R&D and design tool penetration (%)	52	58	72	84
	Key process control rate (%)	27	33	50	64

As a consequence, although smart automation provides great potential and possibilities for realizing future goals, the adaption and adoption of smart automation in China is still questionable. Companies are encountering the challenge of clearly defining an implementation strategy for the most appropriate and beneficial smart automation technologies.

1.3 Objective of the Research

The main hypothesis remains that the efficiency of (Lean) production systems can be improved by the application of smart automation technologies from the domain of CPPS. An additional hypothesis is that existing approaches do not sufficiently consider the influence of location factors for implementing it into Lean production.

The objective of this work is to establish a method for developing the regionalized implementation strategy of smart automation in assembly systems. Location factors are exposed to intensive competition to provide the most attractive conditions for companies. Therefore, location factors play a significant role in improvement actions. Due to the specific development of holistic production systems in industrial companies, interdependencies of smart automation technologies and location factors as well as KPIs are carried out and form a basis for analyzing the appropriate implementation strategy.

Thus, there are two leading research questions:

1. How can interdependencies among smart automation technologies, location factors, and KPIs be analyzed and modelled?
2. How can the most advantageous smart automation technologies for a specific assembly system be selected, considering the effects of location factors?

Thus, modeling the interdependencies are emphasized as opposed to modeling smart automation itself. The consideration of location factors remains the primary motivation at the root of the leading questions. The questions related to the development of a method to support the development of an implementation strategy of smart automation technologies within assembly systems and considering location factors remains relevant.

1.4 Structure of this Work

The structure of this work is composed of seven sections, which are depicted in Figure 1-2. Following the motivation and research objective in Section 1, the essential basics for the understanding of the work are introduced in Section 2. In Section 3, existing research approaches in the literature are reviewed, which concern smart automation, location factors, and KPIs relevant to this work. Research deficits are derived on the basis of evaluation criteria. In Section 4, an approach for achieving the objectives is presented. Its prototypical simulation implementation and validation in the application area of hydraulic engineering is conducted in Section 5, followed by an evaluation of the approach and an outlook in Section 6. Finally, Section 7 concludes with a summary of the work.

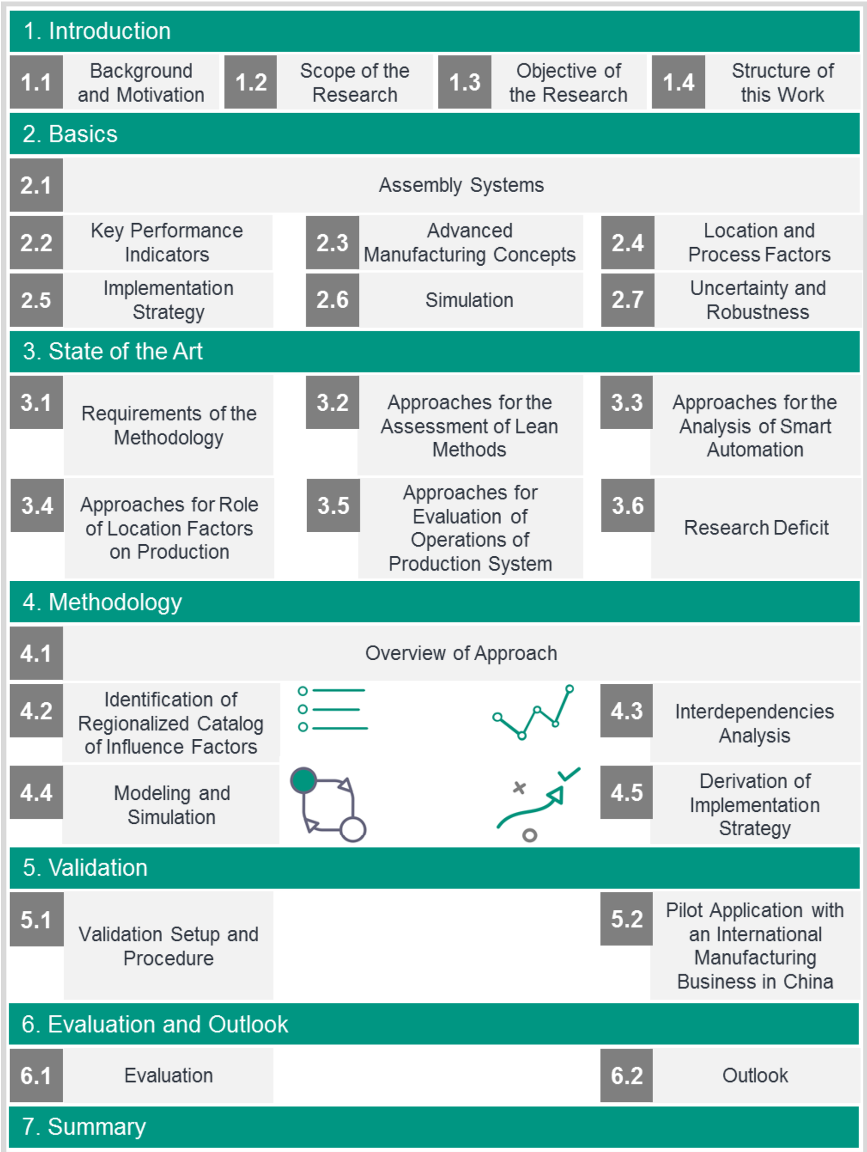


Figure 1-2: Structure of this Work

2 Basics

In this section, the basics of the author’s approach are introduced. In the context of this work, the assembly system is considered as the scope of application. Since the interdependencies of smart automation, location factors and KPIs are key inputs for the derivation of an implementation strategy, it is necessary to clarify the basics of these three factors. Besides the two points mentioned above, uncertainty and robustness as well as simulation are also explained, since they are the basics for better understanding and analyzing the implementation strategy.

2.1 Assembly Systems

Assembly is the capstone process for product realization where component parts and subassemblies are integrated together to form the final products (Hu & Ko et al. 2011). It is an important step in product manufacturing and directly affect the quality of products (Liu & Ma et al. 2017). An assembly system is one of the subsystems in a factory, where the individual components of a product are joined together and thus integrated into a semifinished or into the final product (Butala & Mpofu 2020). The basic assembly system representation is introduced in Figure 2-1. Additionally, assembly systems are primarily classified as manual assembly lines and automated assembly lines, whereas hybrid assembly systems have been developed such as flexible assembly systems, reconfigurable assembly systems, adaptable assembly systems, and agile assembly systems to deal with product variety.

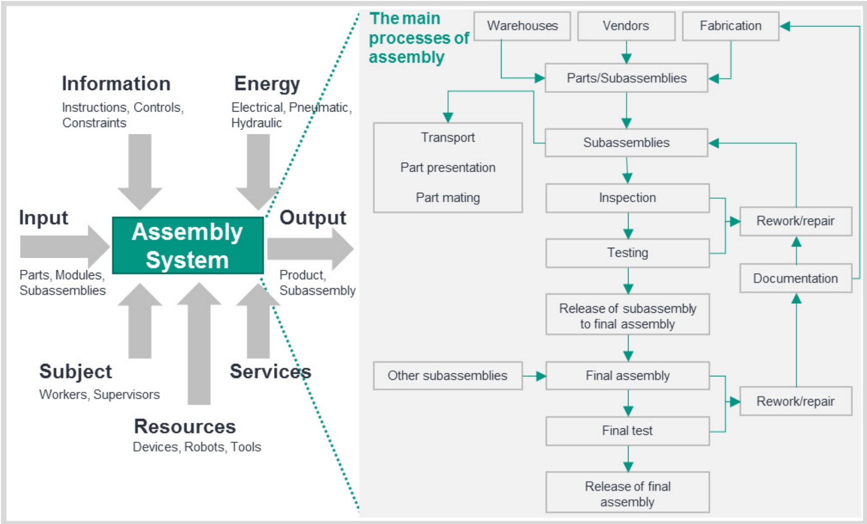


Figure 2-1: Overview of basic assembly system (Butala & Mpofu 2020)

Assembly system design defines proper configurations and efficient management strategies to maximize the assembly system performance. Furthermore, assembly system design has to consider the industrial environment in which the system operates (Bortolini & Ferrari et al. 2017). Some of the most influential management concepts have their origin in the organization of assembly systems, from Henry Ford's assembly lines and the concept of mass production, to the more recent Toyota Production System and the principles of Lean manufacturing. Currently, assembly systems are experiencing dramatic changes imposed by shifting market conditions and profound developments in existing technologies (Battaïa & Otto et al. 2018).

Modern assembly systems are comprised of a large number of entities (machines, transporters, buffers, data, infrastructure, etc.) and have high dimensionality, redundancy, and uncertainty, and many interactions (Hu & Ko et al. 2011). The adoption of Industry 4.0 enabling technologies in production systems has a disruptive impact and improves the factory's technical, economic and social performance. In particular, the integration of these technologies in the design and management of assembly processes leads to the here defined *Assembly System 4.0* (AS40). The application of the IoT technology to assembly processes is the keystone of Assembly System 4.0 (AS40). Every workstation, storage location, piece of equipment, product, worker and generic entity of the Assembly System 4.0 (AS40) is sensorized in order to communicate specific data in real-time (Bortolini & Ferrari et al. 2017).

2.2 Key Performance Indicators

Key performance indicators (KPIs) are financial and nonfinancial measures that are used to define and evaluate the success of an organization. KPIs differ, depending on the nature of the organization and the organizational strategy; they are devised to help evaluate the progress of an organization toward achieving its long-term goals and fulfilling its vision (Abujudeh & Kaewlai et al. 2010). Each company has its own industry- and supply-dependent focus, and accordingly, the requirements for KPIs as well as the basic selection of data to be recorded and evaluated are different (Scholz 2017). A typical KPI hierarchy presented in Figure 2-2, in which KPIs are divided into three categories regarding three different orientation.

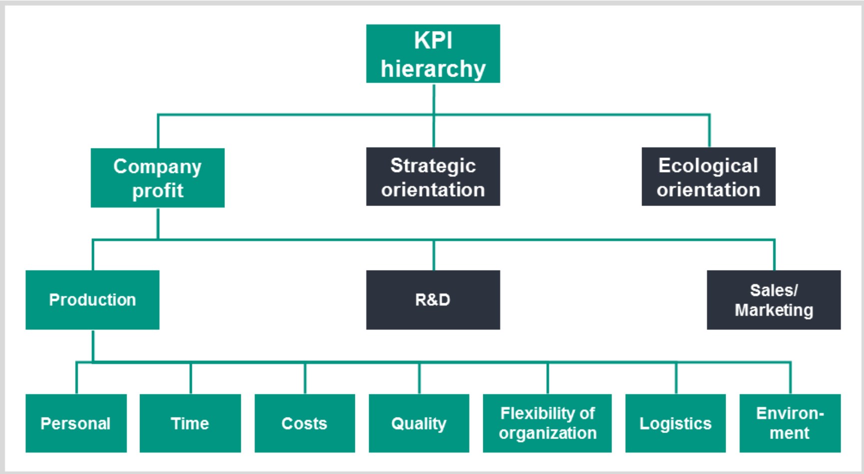


Figure 2-2: Typical KPI hierarchy (AWF[1])

A production process involves several business and technical activities on and around the factory floor. Its effectiveness can be assessed using information hidden in a set of current and historical production data. The problem of extracting the relevant information from production data for fast and accurate decision-making can be solved by introducing a set of production KPIs that show the operational and mid- term efficiency of the production (Badawy & El-Aziz et al. 2016). On the strategic management level,

[1]AWF Arbeitsgemeinschaft für Wirtschaftliche Fertigung, https://www.awf.de/wp-content/uploads/2014/12/Kennzahlen-in-der-Produktion-awf.pdf [14.10.2020]

the problem of overall business efficiency in a production factory is already being solved with this approach (Brown & Debusk et al. 2003), while on the production management level, the implementation of KPIs is a rather new concept. In the field of production, more than 150 KPIs exist (Stricker 2016). It is challenging to select the best subset of KPIs to give a clear view on the system's performance, as the selected KPIs must be able to indicate all possible shortfalls in the production system. At the same time, as few indicators as possible should be used (Stricker 2016).

2.3 Advanced Manufacturing Concepts

Advanced manufacturing technology (AMT) has different meanings in different situations, but it can be broadly defined as an automated production system of people, machines, and tools for the planning and control of the production process, including the procurement of raw materials, parts, and components, and the shipment and service of finished products (McDermott & Stock 1999). Industry 4.0 in many countries related to advanced manufacturing is becoming important. In this context, the relevant concepts such as lean methods, Industry 4.0, CPS and CPPS as well as smart automation will be introduced in the following.

2.3.1 Lean Production

The Toyota Production Systems (TPS) and its synonym Lean Production was developed by Toyota Motor Corporation in the 1970s (Ōno 1988; Sugimori & Kusunoki et al. 1977). The TPS integrates a set of methods and tools with the management philosophy of completely eliminating the seven forms of waste (*Muda*, in Japanese) and to realize profits through cost reduction (Monden 2012). The TPS defines everything that does not create value as waste, including overproduction, waiting for work, transportation, overprocessing, inventory, motion and defects (Tsigkas 2013).

The depicted overview of Lean Production (Figure 2-3) is the symbol for the Lean Production principles. The triangle roof emblematizes the systematic focus on the customer oriented KPIs for quality (Q), delivery (D) and costs (C) (Lander & Liker 2007; Ōno 1988). The basic approach is the continuous improvement of production by integrating the following principles: 5S, Kaizen, Just in Time (JIT), Jidoka, Heijunka, Standardisation, Takt Time, Pull Production, Man-machine separation, People and Teamwork, and Waste Reduction (Thomopoulos 2016).

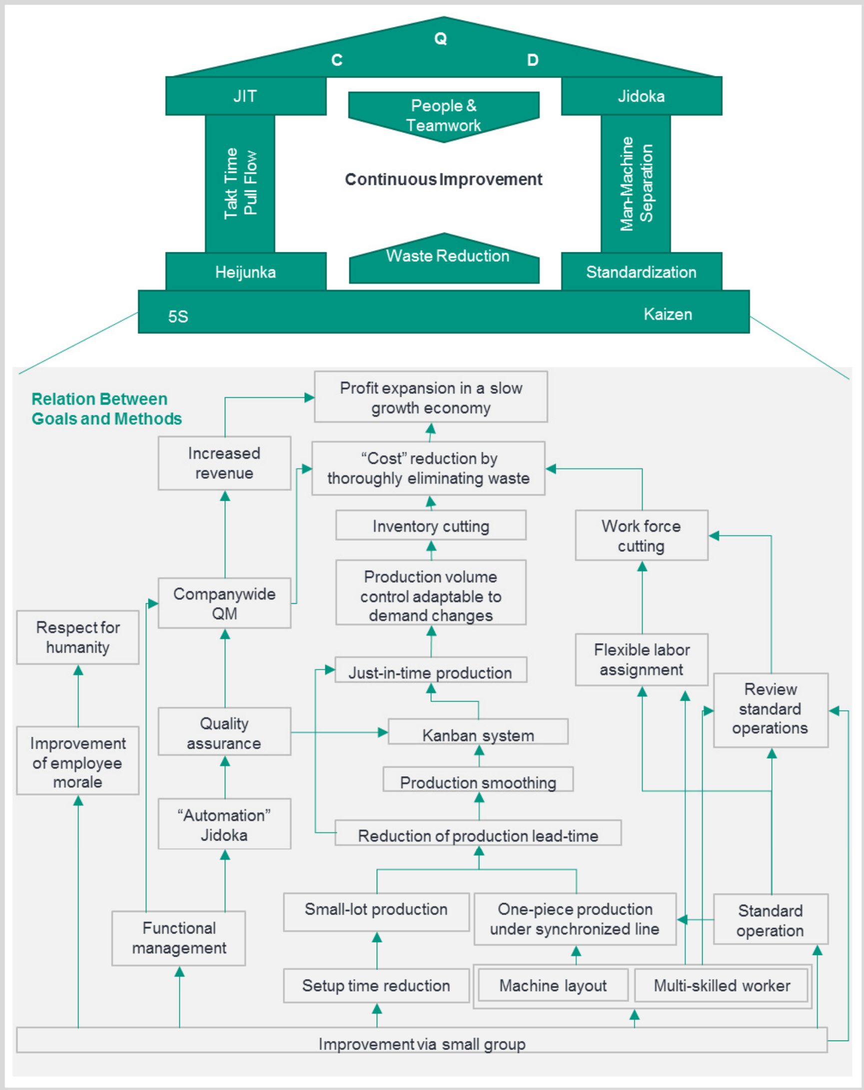


Figure 2-3: Overview of Lean Production (Thomopoulos 2016)

2.3.2 Industry 4.0

The term “Industry 4.0 (I4.0)” was introduced in 2011 to describe the widespread integration of information and communication technology in industrial production (Schuh & Anderl et al. 2017; Roblek & Meško et al. 2016). Although I4.0 has already been significantly developed, it is still hard to uniquely and clearly define it. One of famous definitions states that the term I4.0 stands for the fourth industrial revolution, the next stage in the organization and control of the entire value stream along the life cycle of a product (Kagermann & Wahlster et al. 2013).

I4.0 is ongoing, with the characteristics of Cyber-Physical Systems (CPS), based on heterogeneous data and knowledge integration. The main roles of CPS in I4.0 are to fulfill the agile and dynamic requirements of production and to improve the effectiveness and efficiency of the entire industry. I4.0 encompasses numerous technologies and associated paradigms, including Radio Frequency Identification (RFID), Enterprise Resource Planning (ERP), Internet of Things (IoT), cloud-based manufacturing, and social product development (Lu 2017).

The goals of Industry 4.0 are to achieve a higher level of operational efficiency and productivity, as well as a higher level of automatization. The five major features of Industry 4.0 are digitization, optimization, and customization of production, automation and adaptation, human machine interaction (HMI), value-added services and businesses, automatic data exchange, and communication. These features are not only strongly connected with internet technologies and advanced algorithms, but they also indicate that Industry 4.0 is an industrial process of value adding and knowledge management (Lu 2017).

2.3.3 Cyber-Physical Systems

Cyber-Physical Systems (CPS) are systems of collaborating computational entities which are intensively connected to the surrounding physical world and its on-going processes, simultaneously providing and using data-accessing and data-processing services available on the internet. In other words, CPS can be generally characterized as physical and engineered systems whose operations are monitored, controlled, coordinated, and integrated by a computing and communicating core. The interaction between the physical and cyber elements is of key importance (Monostori 2015).

CPS consist of microcontrollers that control the sensors and actuators. Data and information are exchanged among embedded computer terminals, wireless applications, houses, or even clouds. The complex, dynamic, and integrated CPS in Industry 4.0 will integrate planning, analysis, modeling, design, implement, and maintenance in the manufacturing process (Lasi & Fettke et al. 2014). Because CPS combine information and materials, decentralization and autonomy play important roles in improving the overall industrial performance, CPS are capable of increasing productivity, fostering growth, modifying the workforce performance, and producing higher-quality goods with lower costs via the collection and analysis of malicious data (Lu 2017).

Looking at the development of computer science (CS), information and communication technologies (ICT), and manufacturing science and technology, a parallel development can be observed in Figure 2-4 (Monostori & Kádár et al. 2016).

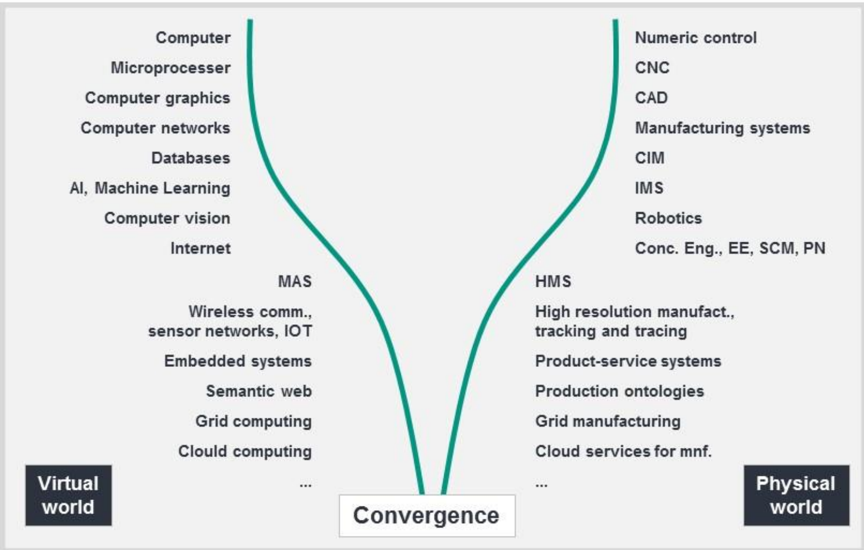


Figure 2-4: Interplay between computer science (CS), information and communication technologies (ICT) and manufacturing (Monostori & Kádár et al. 2016)

2.3.4 Cyber-Physical Production Systems

CPS refer to the convergence of the physical and digital worlds. When applied to production, CPS are specialized in Cyber-Physical Production Systems (CPPS) (Posada & Toro et al. 2015). CPPS partly break with the traditional automation pyramid (left side of Figure 2-5). Even before Industry 4.0, in 2016 Vogel-Heuser & Hess (2016) described how the automation pyramid, which used to be the standard for industrial and automation IT architecture, is evolving into a new kind of architecture of CPS-based automation. It consists of two main functional components by CPPS, which are shown on the right side of Figure 2-5. The lower one is responsible for the advanced connectivity which ensures real-time data acquisition from the physical world and information feedback from the cyber space, while the higher level one incorporates intelligent data management, analytics and computational capabilities that constructs the cyber space (Monostori & Kádár et al. 2016)

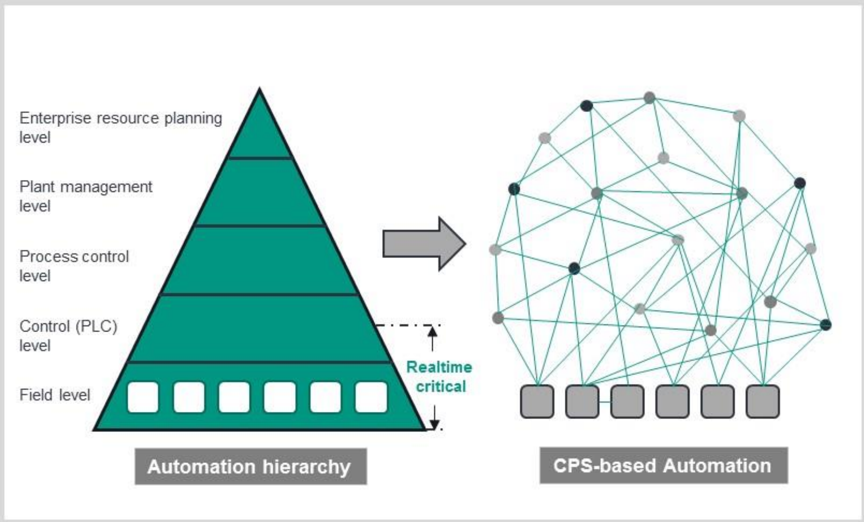


Figure 2-5: Decomposition of the automation hierarchy with distributed services (Monostori & Kádár et al. 2016)

2.3.5 Smart Automation

Smart automation is a process actively supported by smart products, processing high levels of digitalization for automatic monitoring, aiming to take advantage of advanced information and technologies in order to enable flexibility and improve production performance (Yang & Boev et al. 2018). It is derived from other smart concepts, such as smart manufacturing, smart production, smart systems, smart factory, etc. *Enabling technologies* refer to one or a series of wide and multidisciplinary characteristics applied in order to complete tasks (Wan & Cai et al. 2015). In this context, smart automation technologies are identified by six characteristics: real time decision support, transparency, analytics and intelligence, changeability and flexibility, human machine interaction and connectivity. An overview of smart automation is introduced in Figure 2-6.

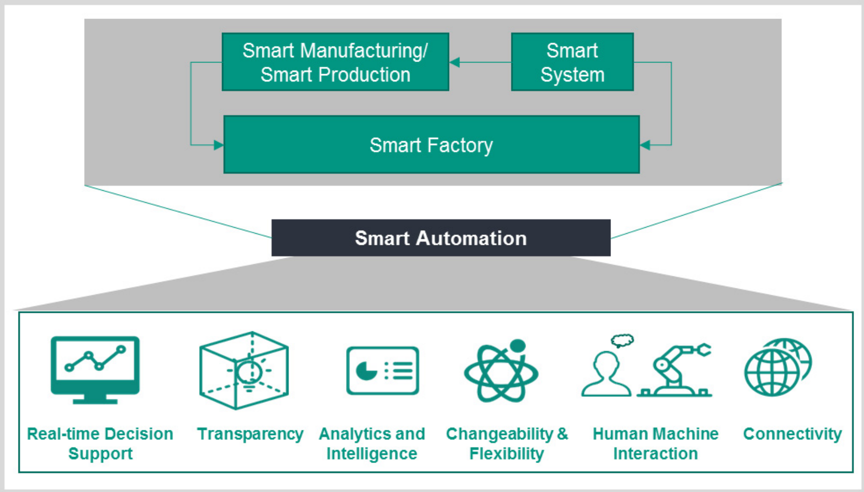


Figure 2-6: Overview of smart automation (Yang & Boev et al. 2018)

Smart Manufacturing and Smart Production

Davis & Edgar et al. (2012) defined smart manufacturing as a broad manufacturing category, the goal of which is to optimize concept generation, production and product trading. While manufacturing can be defined as a multi-stage process of creating products using raw materials, smart manufacturing is a subset of using computer control and high levels of adaptability. Smart manufacturing is furthermore designed to take advantage of advanced information and manufacturing technologies to enable the flexibility of physical processes to respond to dynamic global markets. For this flexibility and the use of technology rather than the specific tasks that are customary in traditional manufacturing.

According to (Wang & Shih 2016), smart manufacturing technology is more common than ever because of continued business fragmentation and the need for overall resource availability. Manufacturers are competing in a global, dynamic market that requires superior quality and service, throughput, innovation, production flexibility, short response times to changing markets, and tight profit margins. With the increase in vitality or uncertainty, manufacturing will gradually move to a distributed environment. In order to win competition locally or globally, the manufacturing system is intelligently prioritized. This leads to digital processing, networked physical system integration and intelligent control on the factory floor.

Smart production is a solution to master the current challenges of today's production by closing the gap between data, technology and process-oriented production design forms. *Production* refers to the interplay of production, information processing and logistics processes, which are supported by development, design, planning and service processes in the sense of smart production systems. The potential of smart production systems results from the effective combination of data-driven, technology-driven and process-oriented approaches. The target concept results in three areas of potential: quality through safety, flexibility through small control circuits and efficiency through minimal administration effort (Birkhahn 2007). The organization model of smart production systems are explained by Birkhahn (see Figure 2-7)

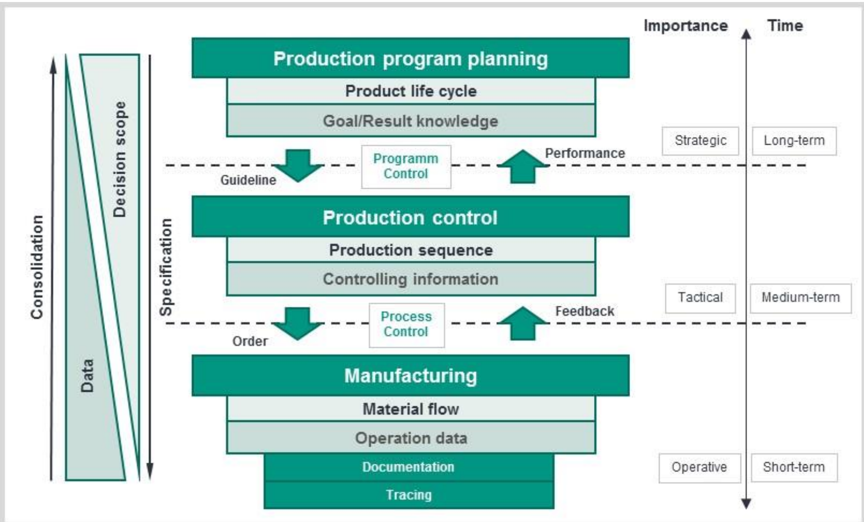


Figure 2-7: Organization model of smart production systems (Birkhahn 2007)

Smart Systems

Harmon & Corno et al. (2015) conclude that smart systems should be instrumented, interconnected and intelligent in order to be effective. First, instrumentation makes the collection of timely, high-quality data through embedded sensors reliable. Furthermore, interconnection enables linkages among people, systems and data and enhance the reality of the systems. Finally, intelligence ensures better decisions and outcomes as well as the reactions of complex systems to emergent demands.

Smart Factories

Radziwon & Bilberg et al. (2014) state the definition of *smart factory.* In the context of the increasing complexity of the world, the smart factory is a manufacturing solution that provides flexible, adaptive production processes that solve the dynamic and rapidly changing boundary conditions problems that occur in production facilities. This specific solution could be related to automation, understood as a combination of software, hardware and/or mechanics, which should give rise to optimization of manufacturing resulting in decrease of unnecessary labor and waste of resource, on the one hand. It can be viewed from the perspective of cooperation between different industrial and non-industrial partners, where the smartness is derived from the formation of a dynamic organization, on the other hand.

Summary

The framework of interoperability of these concepts is showed in Figure 2-8.

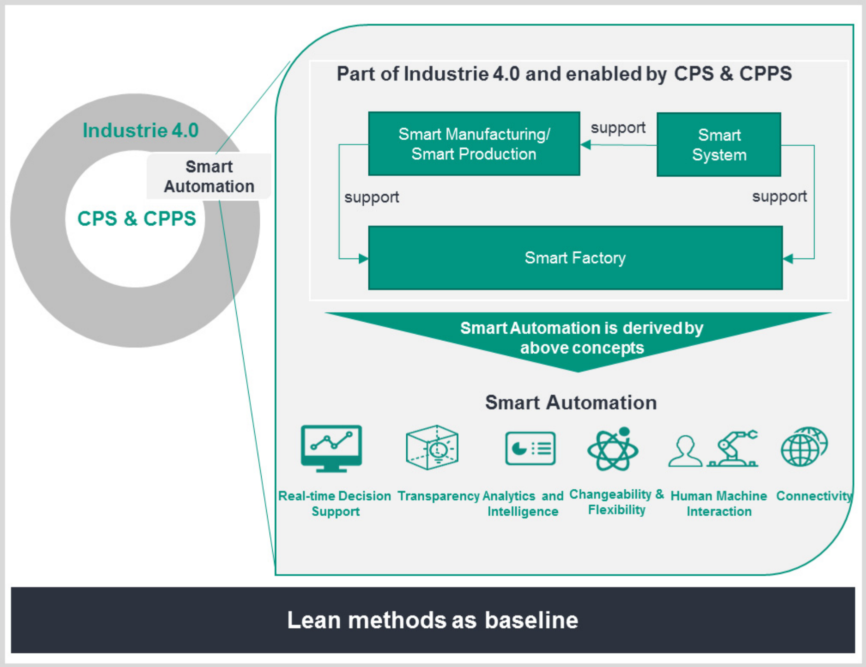


Figure 2-8: Framework of interoperability of basic concepts

2.4 Location and Process Factors

Location theories aim to clarify and to operationalize the process of locational decision-making, for example by analyzing and weighting locational influences and interdependencies of various factors, motivations and conditions, which determine the final choice of location (Winkelmans 1980). Basically, the main problem to be solved is the minimization of production costs (Winkelmans 1980).

2.4.1 Location Factors

Location factors are the economic variables that influence and determine the choice of location (Eckey & Muraro 2008). They reflect the characteristics of a geographic location and influence the attractiveness of a site for a specific process step for a product (Abele & Meyer et al. 2008). Location factors play a decisive role in the choice of a company’s location, since they can have a major impact on the success or failure of a company (Pongratz & Vogelgesang 2016).

It is complex to find one specific general overview of location factors and its classification. However, some classification concepts are often used, such as the division of location factors into market-related or product- and process-related types. The typical quantitative and qualitative location factors of these both perspectives and allocated them to three different consideration levels: global, regional and local (VDI 2012). Besides, location factors can also be sorted into soft and hard ones. Hard factors influence regional dispositions for a particular economic activity with a direct impact on the profit of a particular economic entity. In comparison, the impact of soft factors on economic output is not directly measurable, but they are becoming increasingly significant, as they are getting closer to current trends in economic development (Jirásková 2015).

2.4.2 Process Factors

Abele & Meyer et al. (2008) stated that process factors are the product and production-related factors which describe the manufacturing process and the characteristics of the product. Process factors can be divided into quantitative and qualitative types (see Figure 2-9). Quantitative process factors include the input factor volumes needed to manufacture a product, which depend on the product characteristics and manufacturing technology. Quantitative process factors have a direct impact on total production and logistics costs, while the qualitative process factors have an indirect impact on costs and reveal further location-related requirements, such as a guarantee of uninterrupted supplies or legal safeguards.

Location factors

Factor costs	Labor costs (by skill level)
	Cost of capital
	Cost of materials (parts, raw materials, energy, etc.)
Productivity	Labor productivity
	Capital productivity
Other quantitative factors	Distance from relevant markets
	Potential restructuring and closure costs
	Freight rates
Qualitative factors	Availability of land and infrastructure, rights of ownership
	Legal safeguards, protection of intellectual property
	Regulations, work safety, environmental guidelines, etc.

Process factors

Input factor volumes (quantitative)	Labor time (by skill level)
	Nominal capital employed (plant and equipment)
	Purchased parts/ raw materials
	Parts (made inhouse)
	Space requirements (land and buildings)
Other quantitative factors	Volume and weight
	Dedlivery time requirements
	Maintenance requirements/ costs
Qualitative requirements	Process complexity
	Know-how intensity and sensitivisty/ patents
	Environmental requirements

Figure 2-9: Location and process factors (Abele & Meyer et al. 2008)

2.4.3 Location Criteria

Although some typical examples are given, process factors to be considered in practice should be selected according to the requirements of each specific company and specific production (VDI-Fachausschuss Fabrikplanung 2012). The location criteria is created for a clear interaction between location factors and process factors (see Figure 2-10). For example, labor costs will be the dominant criterion if the products are simple, standard and require labor-intensive manufacturing. However, this is not the case for high-tech products with numerous variants and capital-intensive production equipment. The attraction rate of a particular location for production needs to be evaluated by the requirements for a specific manufacturing step and of a specific product (Abele & Meyer et al. 2008).

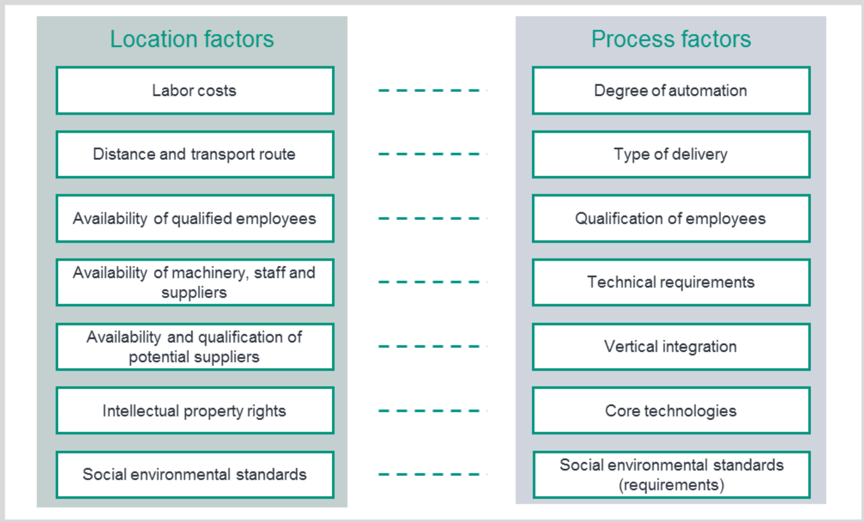


Figure 2-10: Correlation between location factors and process factors (VDI-Fachausschuss Fabrikplanung 2012)

2.5 Implementation Strategy

Wildemann (1987) describes an implementation strategy as a specifically defined procedure. Temporal aspects are especially crucial. An implementation strategy includes concrete implementation times of the individual technologies, which aims to determine the optimal adjustment path from the actual to the target state that proceeds within the limits of the scope of action. The scope of action is specified by temporal, personnel, organizational and financial restrictions.

Investment in advanced manufacturing technologies (AMT) remains a promising but potentially risky venture. Many firms that have adopted these new technologies have not been able to reap all the expected benefits. Since the technical abilities of the AMTs are relatively well-proven, there is a growing belief that managerial issues, from planning to implementation, present the major barrier to employing these technologies effectively (Chen & Small 1994).

Stark (2016) proposes three different strategies from the introduction of Product Lifecycle Management (PLM) methods in the field of production (see Figure 2-11). Path 1 shows that the integration of the PLM methods takes place via continuous improvement, which are already used piece by piece in production during their implementation. This can ensure lasting progress. The method of path 2 is implemented away from the actual production process, because everything changed in year *n*. The integration of the methods occurs in several phases with path 3. Each method is implemented sequentially one after the other, away from the actual production process as well. In contrast to path 2, the introduction in actual production takes place in several phases.

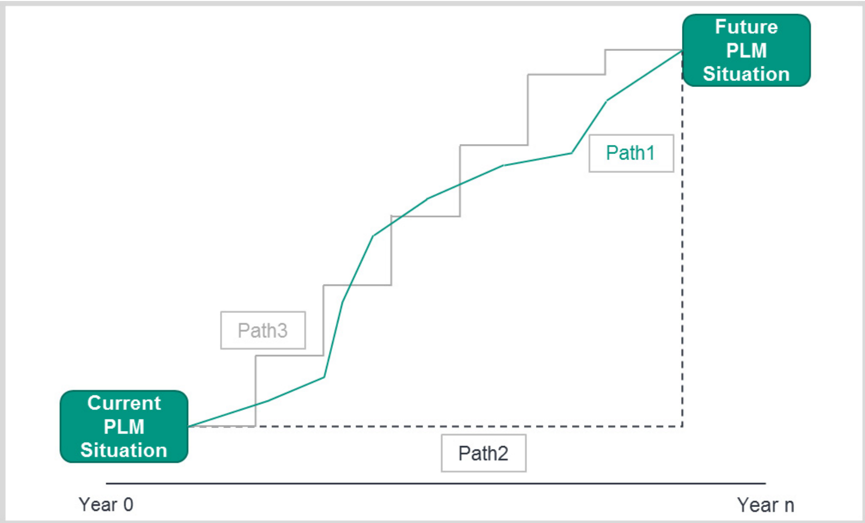


Figure 2-11: PLM implementation strategy (Stark 2016)

The implementation strategy of smart automation is conceptually similar to the PLM implementation strategy.

2.6 Simulation

Simulation modeling is one of the most powerful techniques for researching large, complex systems (Banks 1998). A *model* is a kind of description that abstracts and simplifies the essential parts of the actual system according to the purpose of the research and is an objective reflection of the system. It is used to describe the most basic structure, shape and information transmission of the system. It is an objective portrayal or microcosm of the system.

Simulation is the process of using the model to reproduce the procedure of the real system and through the experiment of the simulation model to research the existing as well as designing system. Thus, a simulation is not a direct experiment on the system, but an indirect experimental analysis of the system by utilizing the model. According to VDI-3633, the procedure of simulation is divided into three phases: preparation, execution and evaluation respectively (see Figure 2-12).

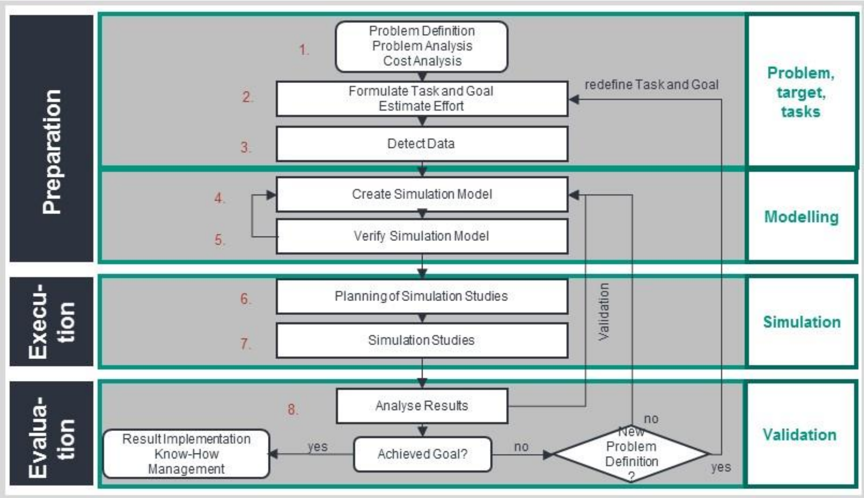


Figure 2-12: Procedure of simulation, according to VDI-3633 Part 1 (2014)

Modeling is the process of producing a model (Maria 1997). A model simplifies the system but still maintains the key performance of the system. One purpose of a model is to enable the analyst to predict the influence of changes to the system. On the one hand, a model should be a close approximation to the real system and incorporate most of its salient features. On the other hand, it should not be too complex to be understood and experimented with. Usually, it is impossible or too impractical to operate what it represents in the system. Nevertheless, the operation of the model can be studied, and hence, properties concerning the behavior of the actual system or its subsystem can be inferred. In this sense, the simulation is a useful tool to evaluate the performance of a system under variable configurations of interest and over long periods of real time (see Figure 2-13).

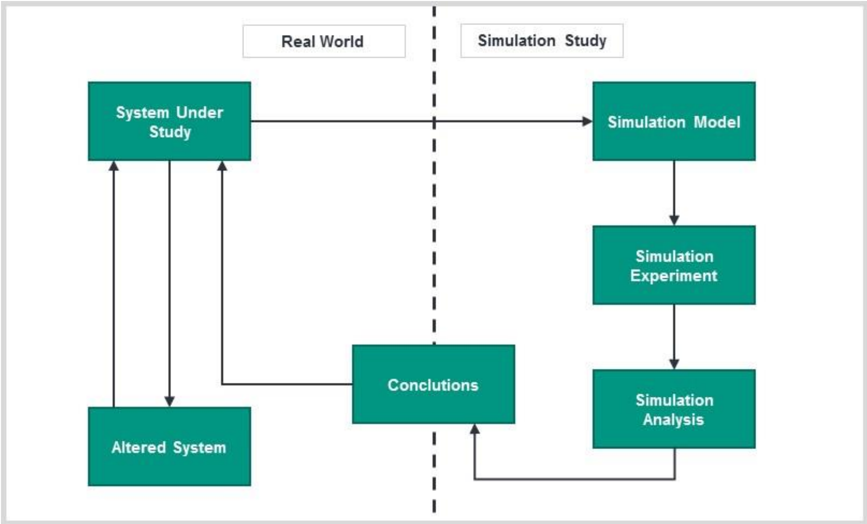


Figure 2-13: Simulation study schematic (Maria 1997)

2.6.1 Hybrid Modeling and Simulation

Borshchev & Filippov (2004) mention that, three different modeling methods have prevailed overall (see Figure 2-14). The degree of abstraction and the way in which the system is significantly different in each method. Hybrid modeling is intended to combine the different aspects of the methods to simulate different levels. Thus, complicated workarounds should be avoided, and the significance of a simulation model should be improved. However, as a rule, a larger modeling effort is required. The following are the three most common modeling methods presented: system dynamics, discrete event and agent based. *Hybrid models* are defined as consisting of at least two different modeling techniques.

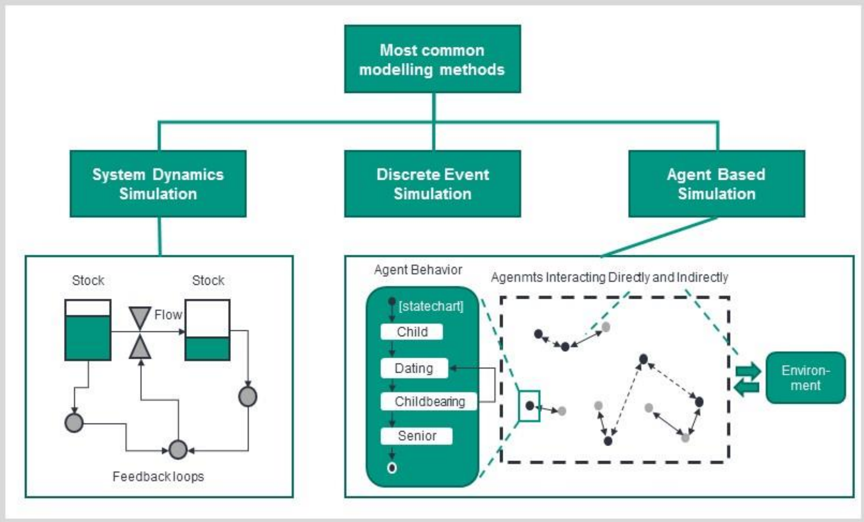


Figure 2-14: Overview of modeling methods (Borshchev & Filippov 2004)

System Dynamics Simulation

System dynamics (SD) was developed in 1958 by Forrester (1958) and is the oldest of the three modeling techniques. Instead of observing a system as a large number of individual objects, these are summarized in so-called *stocks*. This could be, as an example, accumulations of material, knowledge or money. The stocks interact with each other via *flows*, which are mathematically defined by means of auxiliary variables, which create *feedback loops* that either boost or weaken a flow. System dynamics has the highest level of abstraction and is primarily used to analyze the relationships between strategic variables (Sterman 2001).

Discrete Event Simulation

In contrast to system dynamics, discrete event simulation (DES) considers the objects of a system individually rather than as a whole. Each object, such as machines and products, has a state that changes by an event at a discrete time and in turn causes a new event. Accordingly, in a Discrete Event Simulation all scheduled events are stored in an event list with their point-in-times. Newly added events are then dynamically added to the list. Since the execution of an event can influence the point-in-time and thus the order in the list, it will be updated after each event (see Figure 2-15). In other words, the time, which simulated by an arithmetic operation in the DES, varies depending on the events (Bracht & Geckler et al. 2011). *Source*, *delay*, *queue*, *decision* and *sink* are important elements of the DES, this method is particularly well appropriate to production processes, in which the product gradually passes through individual stations (Hedtstück 2013).

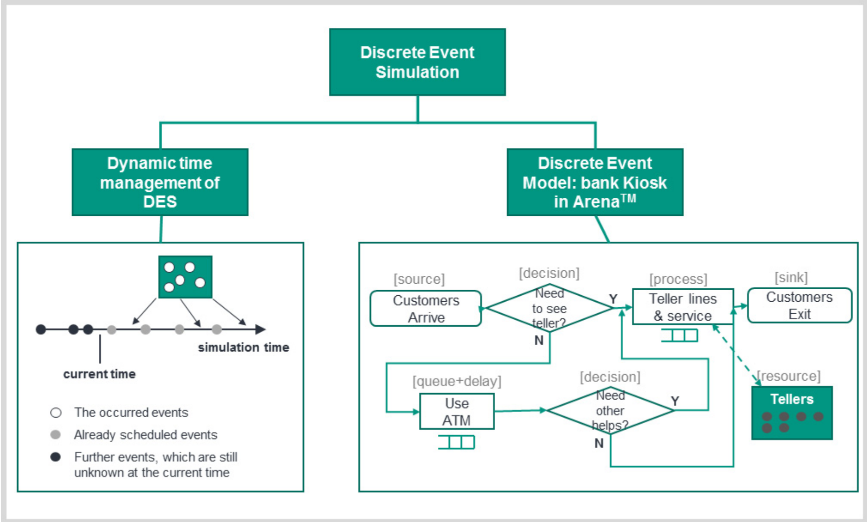


Figure 2-15: Discrete event simulation (Bracht & Geckler et al. 2011; Borshchev & Filippov 2004)

Agent Based Simulation

Agent Based Simulation (ABS) is the latest of the three modeling techniques. It has only been utilized by companies for modeling for about 15 years. The basic idea is that the system behavior is unknown, but the behavior of each element can be described. This happens with so-called *statecharts*. These describe the interaction of the *agent* with other agents or their environment. *Transitions* change the state or behavior of the agent. Instead of modeling each agent individually, multiple instances are created by the same agent.

2.6.2 Modular Simulation

The term *modular simulation* generally refers to the utilization of interchangeable components or modules in a model (Muetzelfeldt & Massheder 2003). The component could be a single function, but it is usually a large component, for example a plant submodel or a soil water submodel. Its advantages include that it would enable the modeling process in terms of model construction, testing and reusability of components. The purest form is *plug and play*, where the interface between the module and the main model is predefined, for example, pins on an integrated circuit chip. What the modeler needs to do is load the module, which automatically becomes a part of the main model.

Kübler & Schiehlen (2000) illustrate that the advantages of the modular modeling are the independent and parallel modeling of subsystems on the one hand, and the easy exchange of results in modules to the use of different software for each module on the other hand. In other words, the exchange and modification of a subsystem is independent of any other component of the main system. Each engineering discipline has different independent software tools and the internal dynamics of the subsystem could be hidden during the simulation of the global system. For an overall simulation, all subsystems must be coupled to achieve global system behavior. A subsystem could be achieved on several different levels of model description, as an example, a mechatronic systems has been observed.

2.6.3 Metamodeling

Metamodeling is a systematic modeling technique that is an abstract at a high level of the system, which is an approach to reducing the complexity of the simulation model and maintaining the validation of the simulation results. A *metamodel* is a definition of a model about the model, which is a description of building model, semantics of the model and integration and interoperation between models. Metamodels are more abstract than general models, which make them a great performance of solving problems in model integration (Mao & Liu et al. 2002). A model is an abstract description of real-world systems and processes, furthermore, a metamodel is an abstract description of the model. Hence, the concepts used for modeling can similarly be used for metamodel modeling.

Höfferer (2007) introduced a metamodeling hierarchy in the year 2007 (see Figure 2-16). It can be seen that subjects under consideration are represented by models. These are created with help of a modeling language (Favre 2005), that is described by a metamodel which means that a model conforms to a metamodel. Then, metamodels themselves can be created using another modeling language that is described by a meta-metamodel. This chain of metamodels theoretically can be carried on to the *n*-th level. However, the process of creating metamodels is usually stopped at the meta-metamodel layer due to the description of the meta-metamodeling language is reflexive (Höfferer 2007).

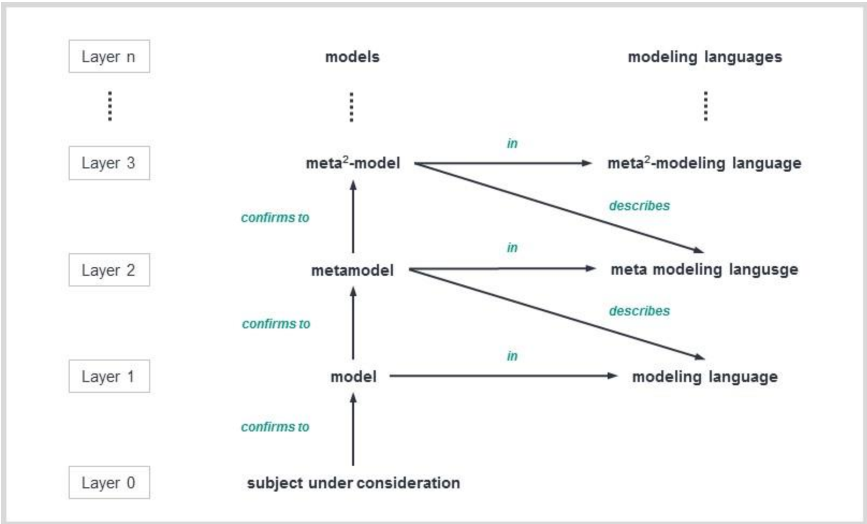


Figure 2-16: Organization of metamodeling hierarchy (Höfferer 2007)

2.6.4 Randomness in Simulations

Simulation models are either *deterministic* or *stochastic*. In deterministic models, the output is "determined" as soon as the input variables and relationships are read into the model and the manipulated variables are defined. The execution of the sequences has no variance. However, many systems must be modeled in such a way that they have at least individual random components. For example, most queueing and inventory systems are modelled stochastically (Law 2014).

The consideration of stochastic components requires knowledge about the type of random distribution. For successful modeling, the correct choice of distribution function is extremely important. Correctness is defined by the real behavior of the component or system (Johnson 1987). For this purpose, the Kruskal-Willis test or tests for measuring the goodness-of-fit can be used. More details on the concrete application of the two tests are described by Law (2014) and are not further relevant in this work.

2.7 Uncertainty and Robustness

Uncertainty has been considered extensively in the context of environmental and hydrological models for many years. In this work, the "VUCA" (Volatility, Uncertainty, Complexity and Ambiguity) will be discussed, which is growing in prevalence in the business literature, and originates from US Military College teachings (Bennett & Lemoine 2014). V*olatility* can be considered as either the deviation from the expected or predicted mean, and a representation of heteroscedasticity, or the occurrence of extreme events/ discontinuities in a future projection (Modarres & Ouarda 2013; Ahmed & Diffenbaugh et al. 2009; Van Notten & Sleegers et al. 2005). Uncertainty, which is closely related to the first condition of the definition of deep uncertainty, considers the unknown range of parametric inputs (Refsgaard & van der Sluijs et al. 2007; Willows & Reynard et al. 2003; Walker & Harremoës et al. 2003). Complexity arises when links between an intervention and an impact are difficult to identify and quantify. High degrees of complexity are common in environmental management and decision-making. Lastly, ambiguity in environmental management can be significant when different stakeholders hold differing beliefs on the level of uncertainty present, the causal relationships and also the preference of management solutions (Maier & Guillaume et al. 2016; Dewulf & Craps et al. 2005).

The meaning of the term *robustness* is used differently in literature. However, there is a common idea of robustness which builds the basis for most of the existing definitions: robustness describes the stability against different varying conditions (Stricker & Lanza 2014).

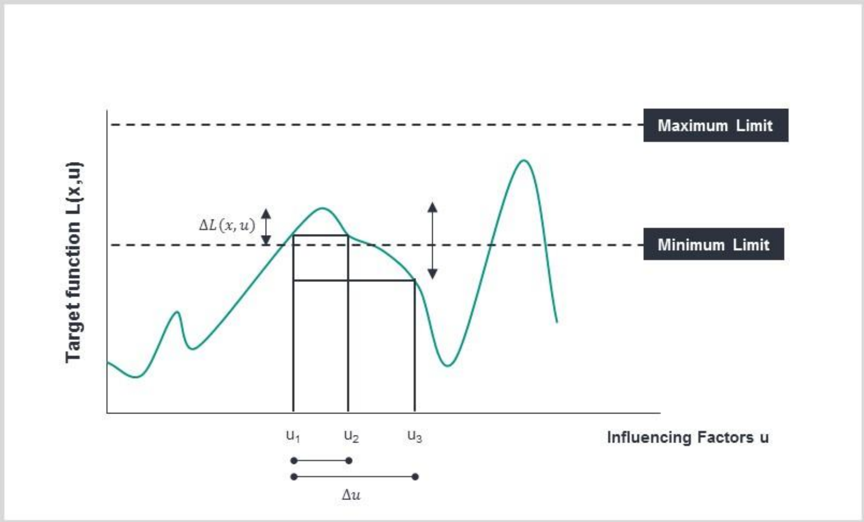


Figure 2-17: Description of robustness according to Stricker & Lanza (2014)

As Figure 2-17 shows, if a possible solution *x* to a problem leads to a stable target function value *L(x,u)* under varying conditions Δu, it is a robust solution. Different authors have different ideas on the demanded stability of the target function value and consider various kinds and scopes of influencing conditions. The influencing conditions Δ*u* have significant effects on the deviation of the target function value *L(x,u).* The more different conditions are considered, the bigger the deviation in the target function value will be. The accepted thresholds in deviation of the target function depend on the author's understanding of stability. Therefore, especially the specific understanding of stability is decisive for a categorization approach of the different ideas of robustness. For all approaches the absolute values of the target value function for different influencing conditions and/or the deviation of the target value function within all regarded influencing conditions is decisive (Stricker & Lanza 2014).

Thus, the robustness refers to the ability of a system to withstand changes without adapting its initially stable structure. In this work, it means that the optimal implementation strategy does not change if input data fluctuates.

3 State of the Art

This section presents a review of existing literature on the topics of location factors, smart automation and KPI analysis for deriving a proper implementation strategy. First, the requirements of the methodology are introduced (Section 3.1). Afterwards, the approaches for the assessment of Lean methods (Section 3.2), analysis of smart automation (Section 3.3), role of location factors (Section 3.4) and evaluation of operation production system (Section 3.5) are accordingly reviewed. The research deficit (Section 3.6) is summarized at the end of this section.

3.1 Requirements of the Methodology

After the knowledge of basics (Section 2), for the formalized research questions and target (Section 1.2), the required methodology can be characterized as follows.

- to take into account the company-specific initial situation such as the relevant location factors and smart automation as well as KPIs
- to qualitatively and quantitatively calculate the interdependencies among location factors, smart automation and KPIs
- to derive an implementation strategy of smart automation technologies

Above three requirements are taken as the criteria for evaluating the existing literatures which have been researched from Section 3.2 to 3.5.

As one of hypotheses, smart automation enhances the Lean Production, it is therefore important to investigate whether there are the approaches for assessment of Lean methods, which considered integration of smart automation technologies to Lean production, especially took influence factors such as location factors and KPIs into account as well (Section 3.2). In order to comprehensively define the potential of smart automation, the approaches for the analysis of smart automation should clearly reviewed, particularly in terms of interdependence (Section 3.3). Since location factors have different impacts on transformation of smart automation, it is required to evaluate the approaches for role of location factors (Section 3.4). In order to quantify benefits of transformation of smart automation, it is necessary to investigate whether the methods are existed to evaluate the effect of implementing smart automation from perspective of production system (Section 3.5).

3.2 Approaches for the Assessment of Lean Methods

There are manifold studies dealing with the assessment of Lean methods. The approaches can be classified according to the degree of implementation based on their potential, as well as the effects of Lean methods. In both categories, qualitative approaches based on surveys and expert estimates, quantitative approaches and graphical approaches can be distinguished. Moreover, there are some recent approaches dealing with enhancing Lean Production through CPPS methods.

Qualitative approaches to assess the degree of conversion and the potential of Lean methods are often based on questionnaires and linguistic assessments (Klemke & Schulze et al. 2009; Nightingale & Mize 2002; Meier & Forrester 2002; Vinodh & Chintha 2011; Bracci & Maran 2013; Chiarini 2014). Quantitative approaches use mostly defined metrics (Srinivasaraghavan & Allada 2006; Bayou & Korvin 2008). Qualitative approaches to assess the impact of the use of Lean methods are largely based on defined indicators such as positive or negative change (Manotas & Rivera 2007; Aull 2013). In the area of the quantitative assessment, there are approaches that take into account operational and financial effects as well as cost-time profiles (Maskell & Baggaley 2004; Rivera 2006; Abdulmalek & Rajgopal 2007; Rivera & Chen 2007; Anand & Kodali 2008; Wan & Chen 2009; Bauer & Horváth 2015; Peter 2009; Al-Aomar 2011; Gupta & Acharya et al. 2013; Jondral 2013; Valero & Barceló et al. 2011; Arbos & Santos et al. 2011).

The approaches to enhance Lean Production through CPPS methods are often focused on data-driven improvements such as supporting the maintenance strategy based on a combination of various data-sets, optimizing machine scheduling based on emergent data using RFID and improving the quality of information used for scheduling. An automated process planner, however, develops service innovations through digitalization and CPS, as well as assists operation processes of employees' through smart tablets (Monostori 2015; Reinhart & Irrenhauser et al. 2011; Nonaka & Erdős et al. 2013; Herterich & Uebernickel et al. 2015; Lage & Filho 2010; Lappe & Veigt et al. 2014). Moreover, Meudt & Metternich et al. (2017) have developed a method to visualize the potential of CPPS in Lean Production Systems based on value stream analysis. Wagner & Herrmann et al. (2017) qualitatively model the effects of different CPPS concepts on various Lean methods. Liebrecht & Bürgin et al. (2016) at wbk suggest an approach for a combined multi-criteria evaluation of CPPS in Lean Production Systems based on a balanced scorecard.

Sanders & Subramanian et al. (2017) focused on studying the possible impacts of Industry 4.0 on Lean management (LM) tools which play a vital role to foster quality and reliability of products and services that are delivered to the customers. The LM tools impacted by the advent of Industry 4.0 and assisting in successful implementation of future smart factories will be investigated in particular focus. An interaction plot matrix is established to quantify the influence of LM tools on Industry 4.0. Interaction between these Industry 4.0 design principles and LM tools reveal several opportunities for achieving synergies, thus leading to successful implementation of future interconnected smart factories. Overall, the work serves as a guideline for industries that are under the transformation phase towards future smart factory and offers space for further scientific discussion.

The existing approaches explained individual applications of CPPS concepts in Lean Production and improved Lean Production by increased information and communication technologies (ICT). However, a systematic method for the implementation of CPPS concepts into Lean Production, considering the influencing location factors, is still missing.

3.3 Approaches for the Analysis of Smart Automation

Since smart automation is part of CPPS field, the relevant research on CPPS are focused on. The following will review the existing approaches CPPS application fields, corresponding maturity levels in these application fields, which form CPPS maturity models, and approaches for interdependency research as well as approaches to design implementation roadmaps based on the assessment results.

3.3.1 Industry 4.0 Readiness Model

The Industry Readiness Model established by Lichtblau & Stich et al. (2015) accomplished the evaluation of the maturity level of Industry 4.0 as a basic backup for self-assessment and comparison of companies. They are able to assess their Industry 4.0 readiness through a series of questions about the state of implementation of Industry 4.0. The model is divided into six dimensions: strategy and organization, smart factory, smart operations, smart products, data-driven services and employees. Each dimension focuses on detailed questions. To classify Industry 4.0 readiness, a six-step model is developed from these six dimensions. Level 0 stands for outsider and level 5 stands for top performer. Accordingly, companies were divided into three groups, namely newcomers, learners and leaders. Beside of defining readiness levels, the model also provides possible obstacles to reaching the next higher level. The consideration of simulation is, regrettably, insufficient.

Monostori & Kádár et al. (2016) established a CPS maturity model which has been divided into five levels: setting basics, creating transparency, increasing understanding, improving decision-making and self-optimizing. Particular reflections in practice are meanwhile mentioned for every single level in this model. At the first level, basic organizational and structural conditions for the implementation is established. The representation of the four higher levels is the maturity of the realizations regarding the information and knowledge processing and the cooperation and collaboration aspects. Information generation represents the need for real-time data availability for all related CPS activities. The existing aggregation instruments are reflected by information processing, which aims to deduce new knowledge. On the two highest levels, namely information linking and interacting CPS, collaboration-based adaptation of CPS processes is emphasized. The final level is the most sophisticated, which can only be achieved by independent problem solving capabilities of collaborative CPS.

Schuh & Anderl et al. (2017) generated the acatech Industry 4.0 Maturity Index, which separates a company's structure into four structural areas: resources, information systems, culture and organizational structure. They identified two guiding principles along with the essential capabilities for each structural area. These capabilities are designed to achieve various stages of development and provide manufacturing companies with the foundation to transform themselves into agile organizations. Additionally, six value-based development stages – computerization, connectivity, visibility, transparency, predictive capacity and adaptability – and the achievement of each stage – provide additional benefits. Schuh & Anderl et al. (2017) also describe the potential development goals and key organizational capabilities required to achieve these levels in different functional areas (development, production, logistics, services, marketing and sales) of the company. Furthermore, the capabilities outlined in the model are consistent with the company's challenges and current activities. The application of the model is also presented through actual scenarios.

Other maturity model and assessment models have been also summarized. For instance, *Toolbox Industry 4.0* was developed by VDMA in order to support companies in generating new ideas in the process of Industry 4.0 implementation (Wang & Wang et al. 2016). The toolbox defines different fields of application of I4.0. Additionally, the RAMI 4.0 provided a reference framework for digitalization and introduced the most important aspects of I4.0 on a three-dimensional map (Platform Industry 4.0 and ZVEI). Lee & Bagheri et al. (2015) define the 5C architecture for the realization of Cyber-Physical Systems (CPS) which serves as a guideline for implementations and realizations of CPS. Furthermore, a generic system architecture was proposed to feature the strengths of the three isolated proposals, such as cross-enterprise data sharing, service orchestration, and real-time capabilities, and can be applied to a wide field of applications (Trunzer & Calà et al. 2019).

3.3.2 Interdependency Research

Brettel & Friederichsen et al. (2014) described the developments of Industry 4.0 within the literature and reviews the associated research streams. Eight scientific literatures with regards to the following research fields were analyzed: individualized production, end-to-end engineering in a virtual process chain and production networks. Cluster analysis was employed to assign sub-topics into the respective research field. Furthermore, to assess the practical implications, face-to-face interviews were conducted with managers from the industry as well as from the consulting business using a structured interview guideline. The results reveal reasons for the adaption and refusal of Industry 4.0 practices from a managerial point of view.

Kleemann & Glas (2017) addressed the actual impact of Industry 4.0 on business and explores the consequences and potentials of Industry 4.0 for the procurement, supply and distribution management functions. A blend of literature-based deductions and results from a qualitative study were used to conduct the research. The sample comprises seven industries and the qualitative method is employed (telephone and face-to-face interviews). The empirical findings indicate that technologies of Industry 4.0 legitimate the next level of maturity in procurement, and support the necessity and existence of the maturity level.

Ciffolilli & Muscio (2018) investigated the comparative advantages of countries and regions in the enabling technologies of Industry 4.0, using data from European participation in collaborative research projects promoted by the 7th Framework Program for research and innovation. Data were regionalized and categorized on the basis of an original taxonomy of technologies developed with the support of a team of European experts in each technological domain.

3.3.3 Implementation Strategy

In current research, most authors pay attention to the implementation of I4.0 technologies on the benefits of value added chain (Bauernhansl 2017), paradigms such as the proper integration of employees (Deuse & Weisner et al. 2015), the implementation of a single technology (Ma & Xu 2017) and the design of the system infrastructure (Wang & Wan et al. 2016). Unfortunately, holistic research does not exist, because the introduction of I4.0 presents specific challenges such as lacking of knowledge about customer demand for new products and business models, difficulties to recognize the starting point and the milestones of the planning horizon, requirements for the prioritization and scheduling of new product and process projects, allocation of limited resources to the projects and cooperation with reliable partners, and lacking of communication about the benefits of Industry 4.0 transformation projects via companies (Vishnevskiy & Karasev et al. (2016) (Dombrowski & Richter et al. 2015).

Thus, in the research of (Liebrecht & Schaumann et al. 2018), various Industry 4.0 methods were analyzed and evaluated for a better selection of those most suitable for a company, especially for small- and medium-sized companies. A structure model for classification and description of Industry 4.0 methods was first established as a foundation of the procedure, containing several aspects and components such as brief description, improvement targets, risks, and internal maturity level. The subsequence interaction analysis of Industry 4.0 methods was also conducted and evaluated, after which the final implementation roadmap can be derived to support strategic decision for companies.

3.4 Approaches for Role of Location Factors on Production

Multiple factors influence which location is best for producing a specific product. There is a large body of literature that has discussed location factors. Hansmann (1974) considered location factors in his work “Decision models for the location planning of industrial companies.” He divided influencing factors into two categories: quantitative factors and qualitative factors. *Quantitative factors* are defined as measurable factors like wages and material costs, exchange rates, quantities, and delivery times (Krebs 2011).

Qualitative factors are often evaluated on a scale from low to high (Brieke 2009). Political stability and educational standards are both examples of qualitative factors.

Dunning (1980) has developed a theory in which international production is divided into six types: resource-based production, import substitution manufacturing, export platform manufacturing, trade and distribution, ancillary services, and other miscellaneous production methods. Each type of international production is influenced by ownership advantages, location advantages, and internalization advantages.

Blair & Premus (1987) reviewed the previous literature on location advantages and concluded that, until the 1970's, traditional location factors, including markets, labor, raw materials, and transportation, were seen as the dominant ones. Later, the dominance of these traditional factors decreased slightly, though it still remained high. Other factors, for example, productivity, education, and taxes also influence location decisions for industrial companies.

Badri & Davis et al. (1995) presented an industrial location analysis in which they developed three models that supplement or complement traditional approaches of industrial location analysis. The models used discriminant analysis in an attempt to reveal the nature of the differences between manufacturers locating in a particular industrial factory and manufacturers who have considered locating in that factory but ultimately did not.

Holl (2004) analyzed the impact of road infrastructure on the location of new manufacturing establishments. It is found out that road infrastructure (in this research, specifically motorways) affect the spatial distribution of manufacturing establishments, with different levels of impact across sectors and space. Cities near new infrastructure tend to have more benefits and be more attractive for new manufacturing plants, even remote from major population and industrial centers.

Badri (2007) has developed a way to select critical factors with the participation of 2,125 industrial firms from 23 countries. He has suggested 10 general critical factors that can influence location decisions: transportation, labor, raw materials, markets, industrial sites, utilities, government attitude, tax structure, climate, and community. He has also suggested four additional factors, namely political situation, global competition, governmental regulation, and economic stability that must be considered when choosing an international location.

Deichmann & Lall et al. (2008) have investigated evidence indicating that location factors have an impact on decision-making regarding industrial locations in developing countries. This evidence implies that the benefits of agglomeration, market access, and infrastructure have stronger effects on location decisions in developing countries than other factors, such as wages and the cost of capital.

The handbook of Abele (2008) focused on the three industries automotive engineering, machine tool manufacturing, and electronics. It looked at the footprint and corporate history of key players, market characteristics, product and production technologies, or cost structure to identify optimal global networks throughout the manufacturing industry. It is important to distinguish between location criteria and the process.

Weiler (2010) has determined nine location-specific factors that have proven to be important for global production, which include labor costs; production equipment and technologies; personnel qualification; infrastructure of logistics; duties and taxes; cultural factors; worldwide coordination; legal protection, piracy and know-how outflow, and dynamics and uncertainties.

Feldmann & Olhager (2013) examined the relationship between site competence bundles and site location. Their research studied the interrelationships among the strategic reasons behind site location choices. They executed a factor analysis utilizing the principal component method and a varimax rotation. They concluded that there are three factors of importance: low costs, markets, and knowledge. Low costs are a result of access to inexpensive energy, proximity to raw materials, and proximity to low-cost labor. The market factor includes proximity to markets and proximity to transport hubs. Knowledge can be evaluated by examining proximity to education facilities and the socio-political climate.

Feldmann & Olhager (2013) and Ferdows (1997) researched the plant roles based on factor analysis and cluster analysis, considering three perspectives: site competence, correlations between site competence and location factors, and the impact on operational performance. They concluded that site competences can be grouped into three bundles: production-related, supply chain-related and development-related. Plants can be classified into three corresponding types, namely plants with only production-related competences, the ones with competences concerning both production and supply chain, and the ones that possess all kinds of competences. Furthermore, the researchers found that the level of site competence has no significant influence on site location decision, but it does have an effect on the operational performance.

Kalantari (2013) outlined location factors that can influence facility location selection for global manufacturing. He cited costs, labor characteristics, infrastructure, other manufacturing locations, regulations, economic factors, quality of life, political factors, and social factors as variables that may have an impact on decision-making.

Ketokivi & Turkulainen et al. (2017) examined 35 assembly location decision cases, especially the ones to locate final assembly purposely in a high-cost country (high Gross Domestic Product (GDP) per capita), from both enterprise strategy and economic policy perspectives. The study examined the linkages between production and other functions, such as product development, market and supply chain, using three key concepts from theories of organization design: formalization, specificity and coupling.

Johansson & Olhager (2018) defined a research model and applied a theory-testing approach in the study, testing how the three major location factors (cost, market, and development competence) related to offshoring and backshoring based on confirmatory factor analysis and regression analyses. The results have verified that these three major location factors are relevant for both manufacturing offshoring and backshoring. The results also indicated significant differences in how these factors influence relocation decisions for offshoring and backshoring as well as how they affect performance.

3.5 Approaches for Evaluation of Operations of Production System

As far as the performance evaluation of production lines is concerned, many different techniques have been invoked, including simulation, Markov chain analysis, approximate analytical methods, and decomposition methods, among others (Liberopoulos 2018).

Conventional performance evaluation systems are based on accounting standards, and characterize information solely on financial terms. However, accounting-based measurement systems have several limitations: they do not allow managers to monitor, control, and improve manufacturing systems continuously. For example, conventional measurement systems present information on financial reports; such data have a considerable time lag and are usually outdated. Moreover, such reports only show previous data and may mislead managers to pursue temporary solutions and ignore long-term improvement (Ghalayini & Noble et al. 1997; Liu 2009; Önüt & Kara et al. 2009). Leong & Snyder et al. (1990) surveyed the literature and generated a composite model for manufacturing performance measurement. This model includes five dimensions: quality, delivery, cost, flexibility, and innovativeness and all dimensions decompose into 37 detailed criteria. Ghalayini & Noble et al. (1997) presented an integrated dynamic performance measurement system that provides an overall view of company performance that helps managers identify areas in their organizations that need improvement. This measurement system has eight criteria: customer satisfaction, integration with customers, quality, delivery, manufacturing cycle time, cost of non-value-added activities, process technology, and education and training. Compared with the model developed by Leong & Snyder et al. (1990), the model created by Ghalayini & Noble et al. (1997) offers broader dimensions concerned with customer relationships and human resource issues.

An effective manufacturing performance measurement system should be both explicit and objective, and provide a means for continuously improving a system. Cost, delivery, flexibility, and quality are the most common dimensions utilized in performance measurement models; each dimension is composed of several detailed criteria. In addition to these four dimensions, customer satisfaction, technology, innovativeness, productivity, inventory, safety and environment, employee morale, and education and training have been considered by different studies addressing specific objectives (Abdel - Maksoud 2004; Ahmad & Dhafr 2002; Chenhall 1996; Ertuğrul & Karakaşoğlu 2009; Lee & Chen et al. 2008; Yurdakul 2002).

Recently, a literature review was carried out in an attempt to determine indicators that are most commonly used. The initial KPIs are constructed using the triple bottom line of sustainability consisting of environmental, economic, and social factors (Amrina & Vilsi 2014). Additionally, an optimization problem for KPI selection was proposed based on the KPI relationships. The constraints of the optimization problem ensured a holistic view on the production system's performance. The determined KPI system was transferred into a quantitative measurement of robustness. From the robustness considerations, various possible improvement actions have been derived and evaluated (Stricker 2016).

3.6 Research Deficit

As the previous sections on the current state of research have shown, effectively implementing smart automation technologies into Lean Production is a strategically significant challenge for companies because different factors should be taken into account in generating the road maps for smart automation transformation. So far, the investigated research approaches only addressed the increase in efficiency by Lean methods and the fields and maturity level of CPPS application. They do not sufficiently consider the influence of location factors for the implementation of smart automation into Lean Production. Furthermore, it clearly indicates the lack of approach that analyzes the interdependencies of location factors and smart automation technologies as well as KPIs. In addition, up to now, a methodology to develop an implementation strategy of smart automation technologies for enhancing Lean Production is still missing (see Figure 3-1).

Therefore, the method to be developed has to take into account the company-specific initial situation such as the relevant location factors and KPIs. Additionally, it should qualitatively and quantitatively calculate the interdependencies among location factors, smart automation and KPIs. In this context, an implementation strategy of smart automation with in-depth analysis for enhancing Lean Production and improving key potentials would be pioneering for academic research and industrial companies to be well prepared in a dynamic corporate environment.

● Fullfilled
◕ Mostly fullfilled
◑ Partially fullfilled
◔ Slightly fullfilled
○ Not fullfilled

Areas (a, b, c, d)	Requirements	Identification of catalog			Interdependency			Implementation strategy		
		Location Factors	Smart Automation	KPIs	Qualitative analysis	Quantitative analysis	Modelling	Simulation	Optimization	Evaluation
a Assessment of Lean Methods	(Meier & Forrester 2002; Nightingale & Mize 2002; Srinivasaraghavan & Allada 2006; Bayou & Korvin 2008; Klemke & Schulze et al. 2009; Vinodh & Chintha 2011; Bracci & Maran 2013; Chiarini 2014)	◔	○	◔	●	◕	◔	○	○	◔
	(Maskell & Baggaley 2004; Rivera 2006; Abdulmalek & Rajgopal 2007; Manotas & Rivera 2007; Rivera & Chen 2007; Anand & Kodali 2008; Peter 2009; Wan & Chen 2009; Al-Aomar 2011; Arbos & Santos et al. 2011; Valero & Barceló et al. 2011; Aull 2013; Gupta & Acharya et al. 2013; Jondral 2013; Bauer & Horváth 2015)	◔	○	◔	●	◕	◑	◑	◔	◑
	(Lage & Filho 2010; Reinhart & Irrenhauser et al. 2011; Nonaka & Erdős et al. 2013; Lappe & Veigt et al. 2014; Herterich & Uebernickel et al. 2015; Monostori 2015; Liebrecht & Bürgin et al. 2016; Meudt & Metternich et al. 2017; Sanders & Subramanian et al. 2017; Wagner & Herrmann et al. 2017)	○	◑	◑	●	◕	◑	◑	◔	◕
b Analysis of Smart Automation	(Lee & Bagheri et al. 2015; Lichtblau & Stich et al. 2015; Monostori & Kádár et al. 2016; Wang & Wang et al. 2016; Schuh & Anderl et al. 2017; Trunzer & Calà et al. 2019)	◔	◕	◔	◑	◑	◔	○	○	◕
	(Brettel & Friederichsen et al. 2014; Kleemann & Glas 2017; Ciffolilli & Muscio 2018)	◔	◑	◑	◕	◑	◑	○	○	◑
	(Deuse & Weisner et al. 2015; Dombrowski & Richter et al. 2015; Vishnevskiy & Karasev et al. 2016; Wang & Wan et al. 2016; Bauernhansl 2017; Ma & Xu 2017; Liebrecht & Schaumann et al. 2018)	◔	◕	◕	◑	◑	◑	◔	◔	◑
c Role of Location Factors	(Hansmann 1974; Dunning 1980; Blair & Premus 1987; Badri & Davis et al. 1995; Abele 2008)	●	○	◑	◔	◔	○	○	○	◑
	(Holl 2004; Badri 2007; Deichmann & Lall et al. 2008; Brieke 2009)	●	○	◑	●	◔	○	○	○	◔
	(Ferdows 1997; Weiler 2010; Krebs 2011; Feldmann & Olhager 2013; Kalantari 2013; Ketokivi & Turkulainen et al. 2017; Johansson & Olhager 2018)	●	◔	◑	◔	●	◔	◔	○	◑
d Evaluation of Operations of Production Systems	(Leong & Snyder et al. 1990; Ghalayini & Noble et al. 1997; Liu 2009; Önüt & Kara et al. 2009)	◔	○	●	◕	◑	◑	○	○	◕
	(Chenhall 1996; Ahmad & Dhafr 2002; Yurdakul 2002; Abdel-Maksoud 2004; Lee & Chen et al. 2008; Ertuğrul & Karakaşoğlu 2009)	○	◔	●	◑	◕	◑	○	○	◕
	(Amrina & Vilsi 2014; Stricker 2016; Liberopoulos 2018)	○	◔	●	◑	◑	◕	◑	◕	◑

Figure 3-1: State of the art of smart automation Implementation Strategy

4 Methodology

Emerging markets are the primary source of growth in the global economy. Economists expect about 70% of the growth in the world economy over the next few years to come from emerging markets. China, as an example of emerging markets, spent more than $279 billion on research and development, constituting the second-largest investment by any single country in 2017. New technologies are creating investment opportunities in emerging markets, and fostering business growth by such as reducing production costs and creating economics of scale (Shankar & Narang 2020).

Essentially the goal is to establish a methodology for developing the regionalized implementation strategy of smart automation within assembly systems in China. The motivated and research leading question in the area of smart automation (see Section 1.2) and the analyzed research deficit (see Section 3.6) delivered the framework for the methodology which is presented in this work. Thus far, the methodology to analyze and model the interdependencies among location factors, smart automation, and KPIs is lacking. Furthermore, a method to derive the implementation strategy of smart automation for a specific assembly system does not exist. Based on this, in order to realize the research target, the developed methodology consists of four main elements, which are introduced in Section 4.1. Subsequently, the procedure of development of methodology is described from Section 4.2 to 4.5.

4.1 Overview of Approach

The approach of this work is composed of four parts (see Figure 4-1). In the first part, the specific location factors, smart automation technologies and KPIs, which are important for China as dynamically developing country, are identified and compiled. Utilizing this information, in the second part, an analysis is defined determining the interdependencies among location factors, smart automation and KPIs. Furthermore, in the third part, the qualitative and quantitative models are established to present the interdependencies based on the hybrid modeling. Considering the outcomes so far, part four provides a procedure to derive an implementation strategy for smart automation for specific assembly systems. Meanwhile, it allows an analysis of the robustness of the aggregate metric of the evaluated simulations.

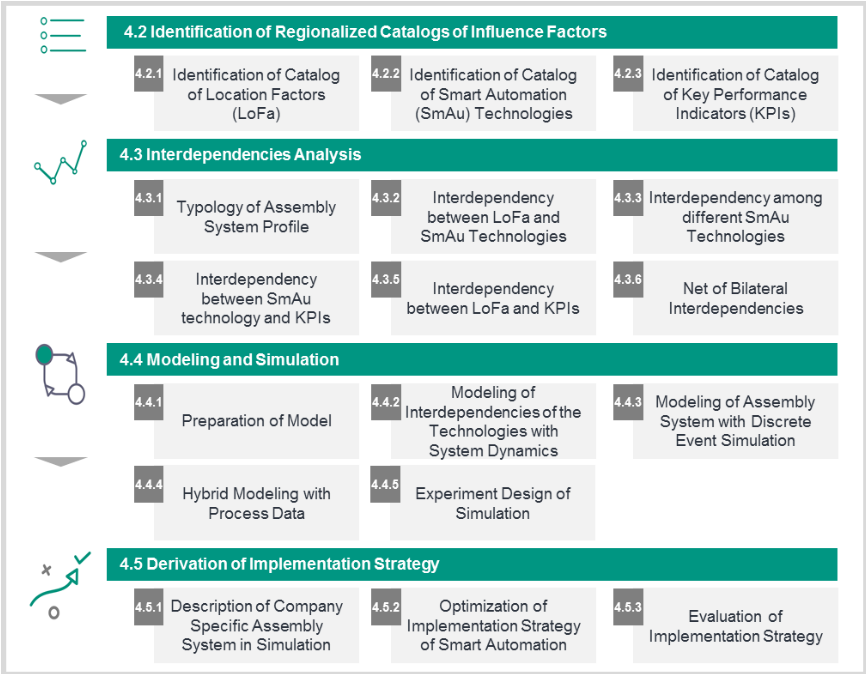


Figure 4-1: Overview of approach

4.2 Identification of Regionalized Catalogs of Influence Factors

This section presents a detailed description of the author’s own research approach regarding the identification of the regionalized catalogs, which consists mainly of three parts. The first part is related to a research on the analysis of the manufacturing location China. In the second part of the approach, a catalog of smart automation technologies is generated. Lastly, the important KPIs are identified according to their significance for China. The output are the integrated catalogs regarding location factors, smart automation technologies and KPIs, which are the core input for further analysis of interdependencies in the next section.

4.2.1 Identification of the Catalog of Location Factors

The aim is the identification of a set of relevant location factors, which play an important role when making a decision to locate a manufacturing facility or technologies investment in China. More precisely, the location factors can strongly influence the smart automation technologies which affect the performance of assembly system. Therefore, the focus of this research is on the different perspectives on relevant location factors for China, as an example of a highly dynamic emerging country.

The proposed approach consists of four steps (see Figure 4-2). First, the scope of relevant location factors is outlined and structured based on existing literature. Second, a questionnaire survey is carried out to study highly important location factors in China. Subsequently, the data analytics are conducted according to the collected survey. Lastly, expert interviews are implemented to verify and modify the output of the previous three steps. As result, the examined catalog of location factors are identified.

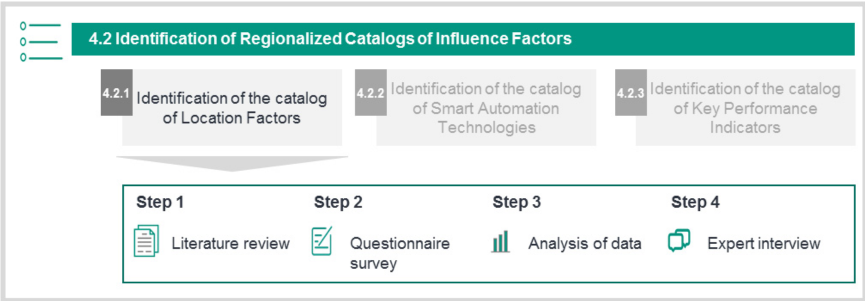


Figure 4-2: Approach for identification of location factors

Literature review of location factors

(Abele 2008; Lanza & Ferdows et al. 2019) have proposed a framework of location factors in regard to global production. In their research, influencing factors are divided into seven aspects: markets and market development, factor costs, logistics factors, cultural factors, political and governmental factors, legal factors, and risks through dynamics and uncertainties. Each aspect consists of several elements. For example, factor costs consist of labor costs, the costs of capital, productivity, material costs and energy, communication, and coordination and support efforts. Logistics variables include deliverability, beside transportation costs and inventory costs. Cultural factors include language and mentalities, educational standards, and staff turnover. Political and governmental factors include taxes, governmental support, trade barriers and duties, non-tariff trade barriers, local content, and other regulations. Legal factors are comprised of the definition of legal systems, the importance of compliance, piracy, know-how protection, patent law, and corruption. Risks through dynamics and uncertainties consist of the effects of exchange rate fluctuation and political and economic stability (see Figure 4-3).

Figure 4-3: Influential location factors related to global production (Lanza & Ferdows et al. 2019)

In addition, several critical influencing factors have been also indicated on the manufacturing industry in China in the past five years, which is based on field research results and a large amount of online survey data (CAFS[1]). There are nine relevant factors: material costs, cost of land, energy costs, labor costs, stuff turnover, transportation costs, capital costs, Taxes and effects of exchange rate fluctuation, respectively (see bold marking in Table 4-1).

To better specify the most influential location factors, the 25 items have been deployed based on above mentioned literatures (see Table 4-1).

Table 4-1: A framework of location factors

No.	Location Factors	Item
1	Market and Market development	• Market size • Market potential

[1]Chinese Academy of Fiscal Sciences, https://www.chineseafs.org/ckynewsmgr/cnpages/cn_index.jsp [19.10.2020]

		• Distance to market
2	Factor cost	• **Labor costs** • **Cost of capital** • Availability of skilled workers • Productivity • **Material costs** • **Energy costs** • **Cost of land**
3	Logistics	• **Transportation costs** • Inventory costs • Deliverability
4	Cultural factors	• Language and mentality • Education level • **Staff turnover**
5	Political and governmental factors	• **Taxes** • Governmental support • Tariff barriers – duty • Non-tariff barriers – local content
6	Legal factors	• Definition of legal system • Importance of the compliance • Piracy, know-how protection
7	Risks via dynamics and uncertainties	• **Effects of exchange rate fluctuation** • Political and economic stability

*The factors marked in bold are coming from CAFS.

Questionnaire survey of location factors

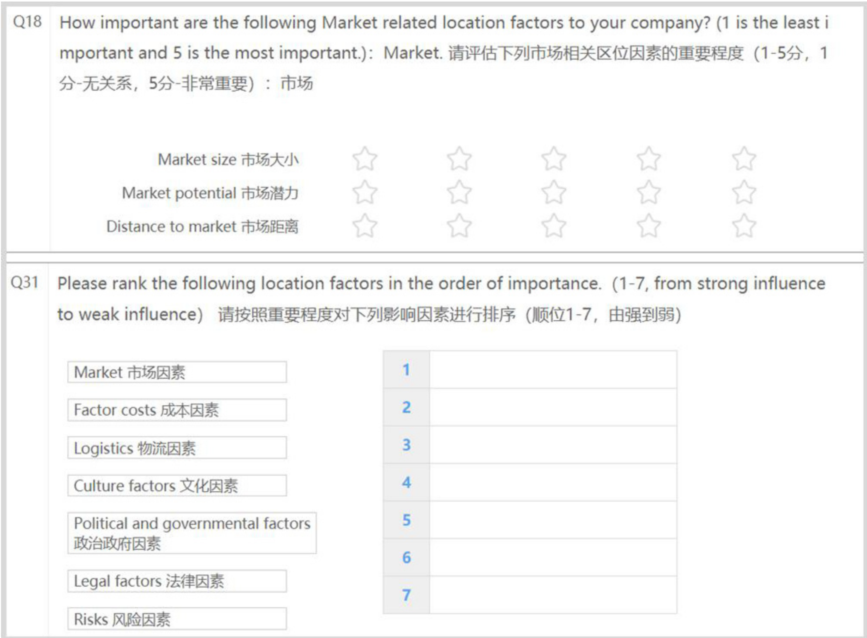
Since the work focuses on existing plants rather than setting up a new plant, the cost of land has not been further considered. After the literature review of location factors, an online survey was designed to assess important location factors. The objective of the questionnaire survey was to gather information from employees in the manufacturing industry. The survey targets employees located in the Yangtze River Delta, the Beijing-Tianjin-Hebei area, and the Pearl River Delta, all in China. These areas were chosen because the industrial situation in these three areas reflects the overall state of industry in the country. The wenjuanwang© platform[1] was selected for conducting the questionnaire. The location factors are identified in this questionnaire survey.

The structure of survey consists of two parts: the basic company information and the ranking of location factors. With regards to the former, the questionnaire is made by general questions such as the complexity of the products produced by the company,

[1]Wenjuanwang platform, https://www.wenjuan.com/ [19.10.2020]

the level of automation of assembly and the proportion of qualified staff in company, etc.

For the latter, the respondents are required to rank each detailed element of seven aspects of location factors, such as the three detailed elements in aspect markets and market development. Afterwards, the seven aspects are required to be ranked by the respondents, too. The scale has been described in each survey question, for example, score 1 is the least important and 5 is the most important (see Figure 4-4).


Q18 How important are the following Market related location factors to your company? (1 is the least important and 5 is the most important.): Market. 请评估下列市场相关区位因素的重要程度（1-5分，1分-无关系，5分-非常重要）：市场

Market size 市场大小
Market potential 市场潜力
Distance to market 市场距离

Q31 Please rank the following location factors in the order of importance.（1-7, from strong influence to weak influence） 请按照重要程度对下列影响因素进行排序（顺位1-7，由强到弱）

Market 市场因素
Factor costs 成本因素
Logistics 物流因素
Culture factors 文化因素
Political and governmental factors 政治政府因素
Legal factors 法律因素
Risks 风险因素

1
2
3
4
5
6
7

Figure 4-4: Example questions related to location factors

To ensure that the questionnaire is target oriented, the respondents are firstly filtered by the following four questions: whether the respondent works in the field of mechanical engineering, whether the company is located in the Heibei/Beijing-Tianjin Region, the Yangtze Delta region or the Pearl River Delta region, whether the company is applying the strategy of Industry 4.0 or a similar strategy, and whether the company conducts the key performance indicators. The evaluation of this questionnaire only takes into account those respondents who answer all four questions. If one of these four questions is not filled, the survey ended for the respondent and the result was automatically eliminated.

Secondly, the basic information regarding the company and job of the respondents was collected. Additionally, the process information regarding production was collected, which will be used to classify the company profile later.

Seventy-nine answers were collected and useable for further investigation. Respondents were asked to answer questions by considering solely their own situations. To confirm the effectiveness of the designed questionnaire, its reliability and validity must be examined (see Appendix A1). Table 4-2 shows that Cronbach's alpha is 0.929, which implies that the questionnaire survey yields reliable results. Table 4-3 indicates that the Kaiser-Meyer-Olkin value for this questionnaire is 0.647, which is greater than 0.6. Meanwhile, the value derived from Bartlet's significance test is 0, which is less than 0.5. These two values indicate that the data are appropriate for use in a factor analysis, therefore, factor analysis is proved to be qualified.

Table 4-2: Overview of reliability of the questionnaire

Case Processing Summary				Reliability Statistics	
		N	%	Cronbach´s Alpha	N of Items
Cases	Valid	79	100.0	.929	55
	Excluded	0	.0		
	Total	79	100.0		
*Listwise deletion based on all variables in the procedure					

Table 4-3: Overview of validity of the questionnaire

KMO and Bartlett´s Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.647
Bartlett´s Test of Sphericity	Approx. Chi-Square	2869.328
	df (Degree of freedom)	1431
	Sig.(Significance)	.000

Since the questionnaire is integrated with content of smart automation and KPIs, the calculation of reliability and validity is omitted in the following Sections 4.2.2 and 4.2.3.

Data analysis of location factors

Data obtained from questionnaires were analyzed in Microsoft Excel^{TM} (see Appendix A2). During this step, a ranking system of all 24 location factors was created (see Table

4-4). It is determined by considering both the rank of the seven aspects and the rank of the constituent items. The final score for each item was calculated by using Formula 4.1, since the influence of seven factors is assigned a value from 1 to 7 (1=highest priority to 7=lowest priority). The influence of the items comprising each factor is scored using a 1–10 scale (1=lowest influence to 7=highest influence).

$$S_i = S_{Ii} \times \frac{1}{S_{Ai}} \qquad \text{Formula 4.1}$$

S_i means final score of each item, S_{Ii} means the score gained of each item in its aspect, S_{Ai} is score of corresponding aspect.

Table 4-4: The rank of all 24 location factors

No.	Location Factors	Value	Remarks
1	Market size	3.866	
2	Market potential	3.731	
3	**Cost of capital**	3.728	Emphasized via expert interview
4	**(Labor) Productivity**	3.649	Emphasized via expert interview
5	**Labor cost**	3.586	Emphasized via expert interview
6	Distance to market	3.561	
7	**Material costs**	3.479	Emphasized via expert interview
8	**Energy costs**	3.428	Emphasized via expert interview
9	**Availability of skilled workers**	3.367	Emphasized via expert interview
10	(Deliverability) Infrastructure	1.918	
11	**Taxes**	1.863	Emphasized via expert interview
12	Inventory cost	1.859	
13	Non-tariff barriers	1.803	
14	Language and mentality	1.802	
15	**Transportation cost**	1.782	Emphasized via expert interview
16	**Staff turnover**	1.751	Emphasized via expert interview
17	Tariff trade barriers	1.746	
18	Governmental support	1.698	
19	Education standards	1.687	
20	Compliance	1.554	
21	Political and economic stability	1.495	
22	Patent	1.452	
23	Effects of exchange rate fluctuations	1.412	
24	Definition of legal systems	1.386	

Expert interviews of location factors

Expert interviews were undertaken to help verify the top location factors obtained from the questionnaire survey. Experts from BSH China, Siemens (SEDL), and three other SMEs (Jiangmen Hunglik, Wanda Foundry Group, GHH Safety Solution) were interviewed. The market related location factors have not been further considered since

China as a whole has the same market situation. Transportation costs have been highlighted by experts in the area of logistics factors. Staff turnover, which poses a very significant challenge for the industry, was also emphasized by experts. The most important location factors identified via the questionnaire were examined once again, taking into consideration suggestions from the expert interviews. In this manner, the most important location factors were identified (see Table 4-5). These findings are employed in the following analysis of interdependencies between location factors and smart automation technologies.

Table 4-5: Catalogue of location factors

No.	Name	No.	Name
1	Labor costs	6	Transport costs
2	Cost of capital	7	Energy costs
3	Availability of skilled workers	8	Material costs
4	Staff turnover	9	Labor productivity
5	Taxes		

4.2.2 Identification of the Catalog of Smart Automation Technologies

The steps used to identify smart automation technologies are the same as those used to identify location factors. A literature review, questionnaire survey, data analysis, and expert interviews are included (see Figure 4-5).

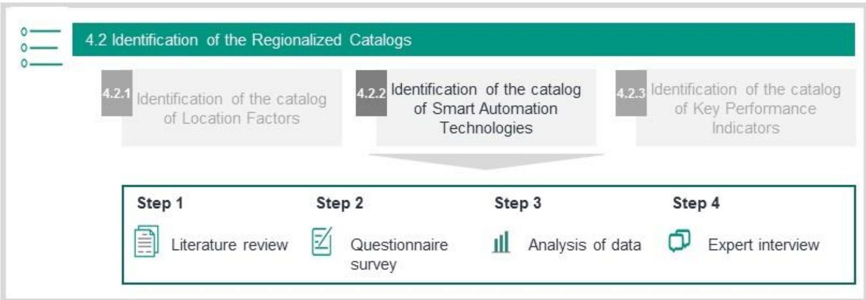


Figure 4-5: Approach for identification of smart automation

Literature review of smart automation

Since smart automation is within the framework of Industry 4.0 or CPPS, the literature review is narrowed down from Industry 4.0 to derivation of smart automation technologies. A three step approach was applied in order to select the smart automation technologies based on literature review (see Figure 4-6:). In the first step, Industry 4.0 technology fields were identified. Second, the generated application map of CPPS was summarized based on the various exemplary Industry 4.0 use-cases from the industry. Third, smart automation technologies, which have also been demonstrated in the testbed at the GAMI[1] Suzhou, were selected as representative.

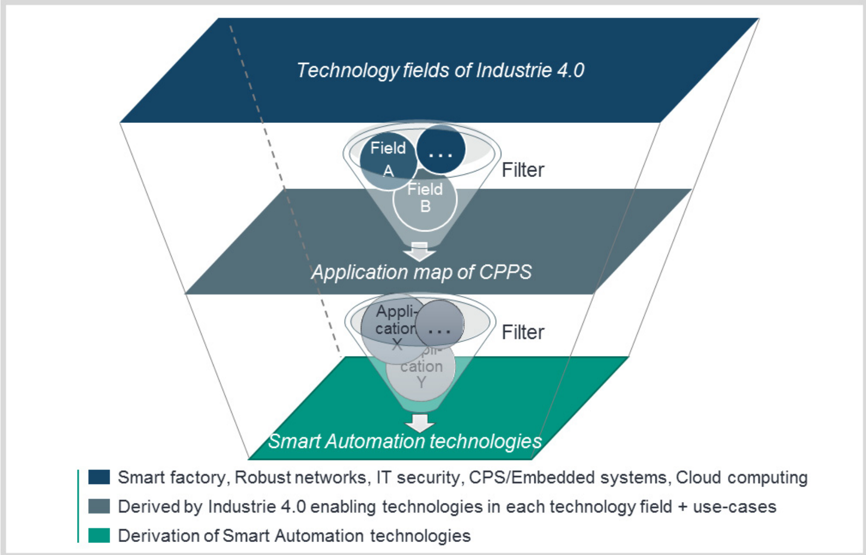


Figure 4-6: The three steps approach for derivation of smart automation technologies

The classification of Industry 4.0 technology fields is selected according to (Bauer & Schlund et al. 2014). The reason is that the industrial domain is addressed in this study and, hence, the proposed classification was found to be appropriate. They identified the following five technology fields which are expected to be highly significant in the context of Industry 4.0: CPS/embedded systems, smart factory, cloud computing, robust networks and IT Security.

The application fields of CPPS were derived based on the study of various exemplary cases from the industry, and summarized in a graphical representation. According to Yang & Boev et al. (2018), the application map of CPPS consists of 29 applications. The generated CPPS application fields are divided into five clusters – manufacturing process, information and computing technology, big data/ cloud, research and development, as well as logistics and supply chain management (SCM). As logistics and supply

[1]GAMI, Global Advanced Manufacturing Institute, http://www.silu.asia/index.php?siteid=2 [15.02.2021]

chain management are closely linked to production systems, various Industry 4.0 applications for logistics and supply chain management were also generated and depicted in the graphical representation below. Nevertheless, the emphasis of this work is on application fields related to production processes and production environments. Therefore, the generated Industry 4.0 applications for logistics and supply chain management will not be further taken into consideration.

The graph below provides a complete overview of the generated CPPS application fields assigned to each cluster, together with Industry 4.0 applications for logistics and supply chain management (see Figure 4-7). The description can be found in Appendix A3.

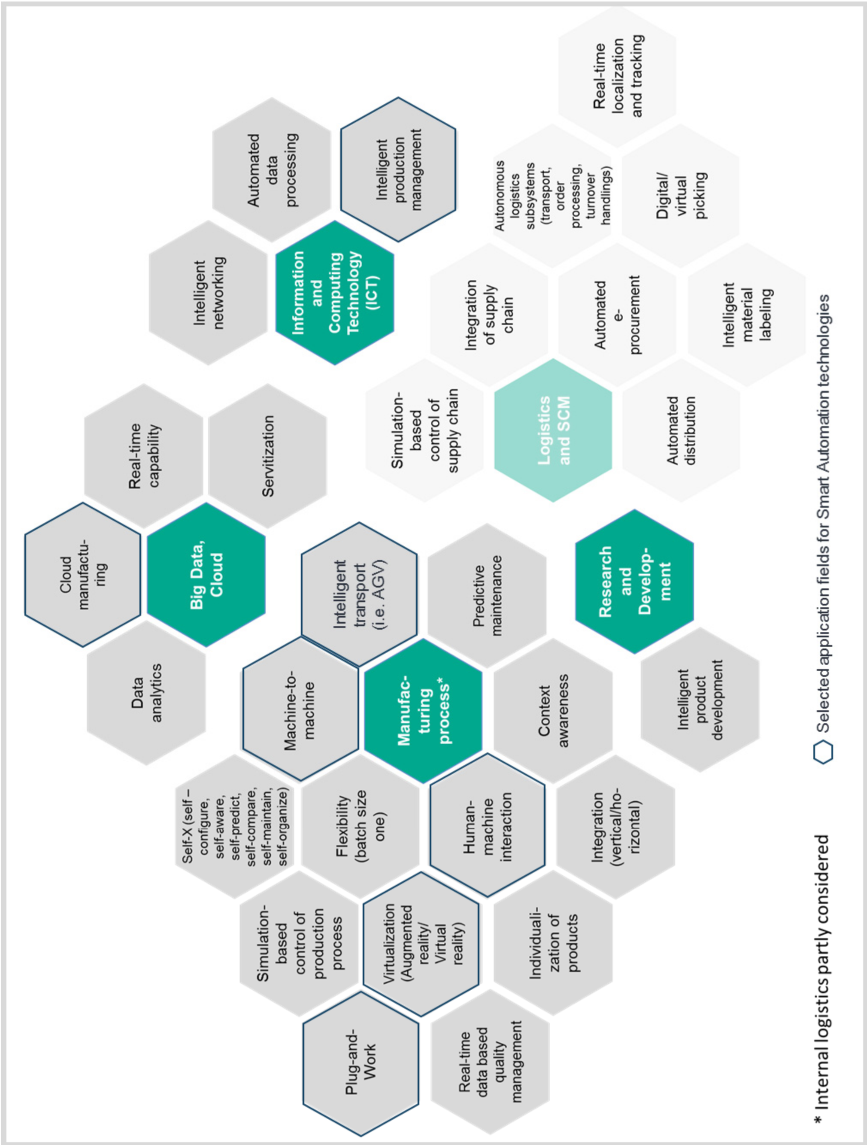


Figure 4-7: Application map of Cyber-Physical Production Systems (A_Boev 2017)

Smart automation technologies in the testbed

Ten application fields of CPPS have been selected for deriving smart automation technologies, namely Plug-and-Work (i.e. Pick-by-Light, Smart gloves), Real-time data based quality management (i.e. Wireless nut runner), Virtualization (i.e. Augmented reality/Virtual reality), Human machine interaction (i.e. Human Machine Interface), Integration (vertical/horizontal, i.e. Workplace carrier with RFID tags, QR-Code,) Machine to Machine (i.e. Automatic torque adjustment, Intelligent screwdriver), Intelligent transport (i.e. Automatic Guided Vehicle), Predictive maintenance, Cloud manufacturing (i.e. Cloud-technology), Automated data processing (i.e. Manufacturing Execution System, Digital Shopfloor Management). These application fields have also been demonstrated in the testbed, which consists of two innovation facilities, respectively the Industry 4.0 Demonstration and Innovation Center and the Artificial Intelligence Innovation Factory located in GAMI Suzhou (Yang & Schrage et al. 2019). The derived 16 smart automation technologies (see Figure 4-8) have further been classified in the six cluster according to Figure 2-6. Based on these smart automation technologies, a questionnaire survey was carried out.

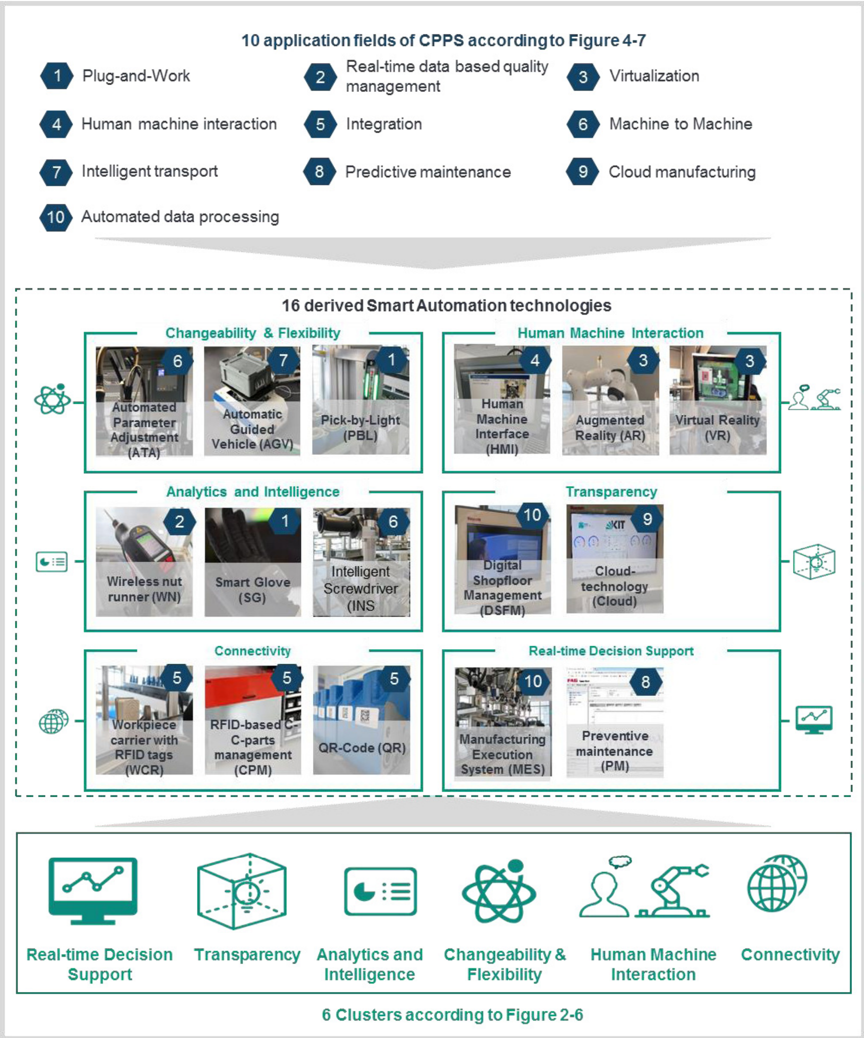


Figure 4-8: Sixteen representative smart automation technologies

Questionnaire about smart automation

Similar as the questionnaire of location factors analysis, the questionnaire asks respondents to evaluate the importance of the 16 smart automation technologies by providing each with a score between 1 and 10 (1=least important to 10=most important) (see Figure 4-9).

Figure 4-9: Question related to enabling technologies of smart automation (A_Yu 2018)

Data analysis of smart automation

The 79 piece of feedback were collected and analyzed. The average value of each smart automation technology was calculated and the results are shown in Figure 4-10. It is difficult to distinguish the most important smart automation technologies as there are only minor differences among the 16 selected. The scores of evaluation are between seven and eight. Expert interviews could be further conducted to figure out a catalog based on 16 smart automation technologies.

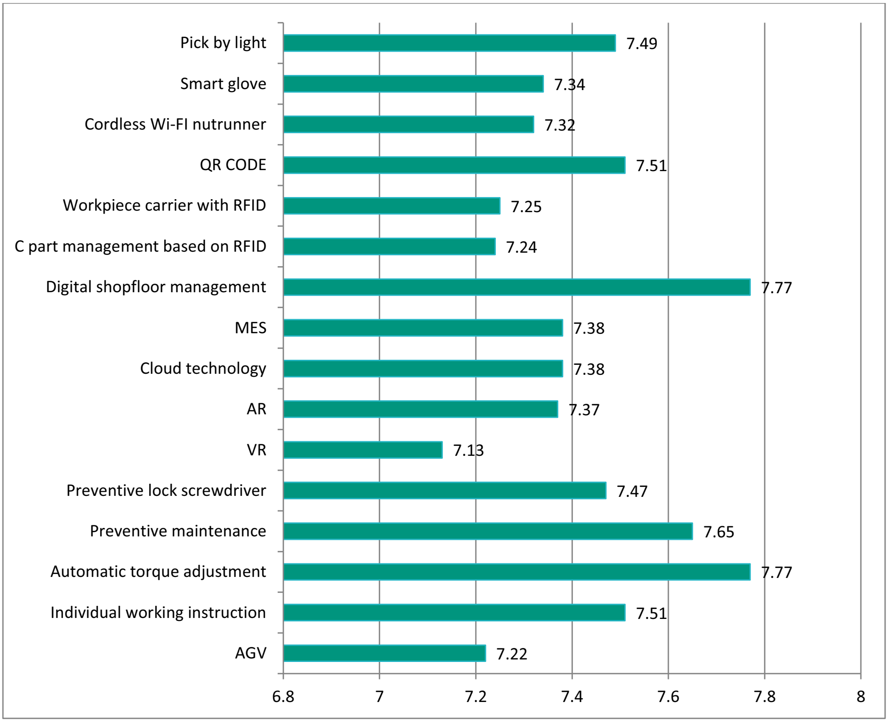


Figure 4-10: Evaluation of importance of smart automation technologies

Expert interviews

The experts for analyzing smart automation technologies were the same as for location factors. Similarly, the experts were required to rank 16 enabling technologies applied in assembly systems. Cloud technology was not further considered since it focuses on network level rather than assembly systems of a factory. Although predictive maintenance has gained a lot of attention, it is still crucial due to the immaturity of this technology (Compare & Baraldi et al. 2020). In fact, predictive maintenance depends on accurate data and it needs to be empowered with data science capabilities. A false alarm triggered by inaccurate data can lead to incorrect actions and additional costs. Therefore, predictive maintenance was not taken into account in the present research. The virtual reality (VR) and augmented reality (AR) has been emphasized in the industrial applications fora long time, however, there are many challenges yet to overcome before adoption goes truly mainstream, including stability in a dynamic environment and latency. Thus, virtual reality (VR) and augmented reality (AR) will not be further considered either.

By combining suggestions from experts and the results of the questionnaire survey (see Figure 4-10), the most important twelve smart automation technologies were finally identified as the input for the further analysis (see Table 4-6). Based on information collected from technology providers and the author's own preliminary experiments, profile descriptions for the technologies were generated (see Appendix A4). This will be used as background knowledge of research in the following Sections.

Table 4-6: Catalogue of smart automation technologies (A_Guo 2019)

No.	Name	No.	Name
T1	Pick-by-Light (PBL)	T7	Automatic torque adjustment (ATA)
T2	Human Machine Interface (HMI)	T8	RFID-based C-parts management (CPM)
T3	QR-Code (QR)	T9	Workpiece carrier with RFID tags (WCR)
T4	Intelligent screwdriver (INS)	T10	Digital Shopfloor Management (DSFM)
T5	Wireless nut runner (WN)	T11	Manufacturing Execution System (MES)
T6	Automatic Guided Vehicle (AGV)	T12	Smart gloves (SG)

Figure 4-11 provides an example of the technology profile regarding a Wireless nut runner. It consists of a picture and a brief description of the main functions and operating principles, as well as the category its main benefits, which help to understand the technology more clearly. Profiles of the other eleven relevant technologies are also shown in Appendix A4.

Wireless nut runner (WN)

Picture	Description
	A Wireless nut runner (e.g. Bosch Nexo) features a fully integrated logic controller, which monitors all the torque and rotation angle of the tightening action. These process data are displayed instantly to let the user know if the tightening has been successful along with other key information. In addition, the data are sent wirelessly to local devices or a cloud platform, where the real-time data will be automatically analyzed and visualized to show process anomalies.
Category	**Benefits**
Changeability and Flexibility	▪ Process reliability ▪ High-precision measurement ▪ Rapid information availability

Figure 4-11: Profile of Wireless nut runner (A_Guo 2019)

4.2.3 Identification of the Catalog of Key Performance Indicators

There are four steps (see Figure 4-12) to identify the catalog of key performance indicators in this Section. A KPI structure was generated from relevant production KPIs, which explicitly show the performance of the assembly system with an overview perspective, and corresponding process data, which can be directly collected from practical cases and be used for calculating the KPIs. In addition, related intermediate parameters are also integrated if needed.

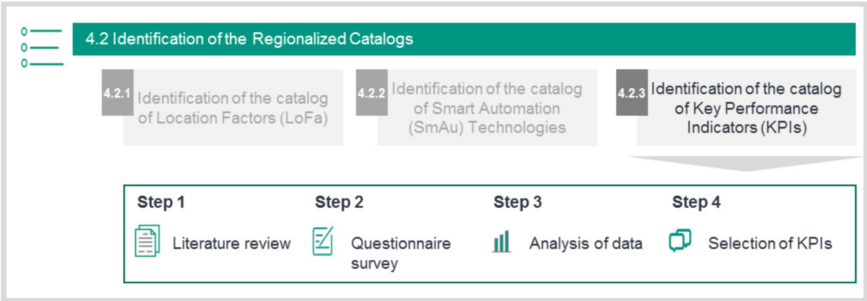


Figure 4-12: Approach for identification of KPIs

Literature review of KPIs

In the field of production, more than 150 KPIs exist. It is a challenge to select the best subset of KPIs in order to give a clear view of the system's performance (Stricker 2016). At the same time, as few indicators as possible should be used. Considering this point, sixteen KPIs (see Table 4-7) have been selected based on a literature review and investigation of several industry companies like Continental, Red Lion, Volkswagen, Huihong (Bauer & Hayessen 2009) (see the Appendix A5).

Table 4-7: Sixteen selected KPIs (A_Yu 2018)

No.	Name	Reasons
1	Overall Equipment Effectiveness (OEE)	Overall Equipment Effectiveness (OEE) is one of the most important performance measurements in modern manufacturing facilities, by optimizing OEE, the production capacity-ty can be increased.
2	Overall Labor Effectiveness (OLE)	Overall Labor Effectiveness (OLE) expands the concept of OEE by quantifying, diagnosing, and predicting not only the performance of the workforce and its influence on production, but the connection between the employees

		and the resources needed to expand production.
3	Labor Productivity	Labor productivity is the most commonly used measure which indicates the number of units produced relative to employee labor hours.
4	Transparency	Transparency is an essential condition for full availability and access to information required for collaboration and collective management decision-making.
5	Lead time	Lead time is an important factor for customer satisfaction.
6	Material availability	Material availability is an important factor which can have a lot of consequences for the companies, like delay, rework, increased work in process etc.
7	Set-up time	Set-up time is an important operation factor which determines how flexible a production process is.
8	Cost (storage, transport, production, maintenance, inventory)	Cost (storage, transport, production, maintenance, inventory) is critical to any company.
9	Flexibility	Flexibility is a key factor for efficiently improving market responsiveness in the face of uncertain future product demand.
10	Scrap rate	Scrap rate is a common KPI since it indicates how quality performance is.
11	Customer satisfaction	Customer satisfaction plays a crucial role to lead a realization of development of the company.
12	Reaction speed	Reaction speed facilitates the agility of production operation.
13	Machine availability	Machine availability is an important factor which can have a lot of consequences for the companies, like delay, rework, increased work in process, etc.
14	Return on investment (ROI)	Return on investment is a useful metric for evaluating overall savings or revenue increases.
15	Revenue	Revenue is important to justify the fixed and variable expenses
16	Net cashflow	Net cashflow is important to determine business performance

Questionnaire about KPIs

The importance of the different 16 KPIs were structured in the questionnaire and evaluated with a score between 1 and 10 (1=less important, 10= very important). More details can be found in Appendix A6.

Data analysis of KPIs

Since the survey is combined with data from the previous sub-Sections 4.2.1 and 4.2.2, there are also 79 respondents for the selected KPIs. On the basis of an average score, a higher number means more important KPIs for production in China within the bar chart (see Figure 4-13). Meanwhile, as Figure 4-13 showed, there are minor differences of importance among the investigated 16 KPIs. It was therefore challenging to select the representative KPIs out of ranking result.

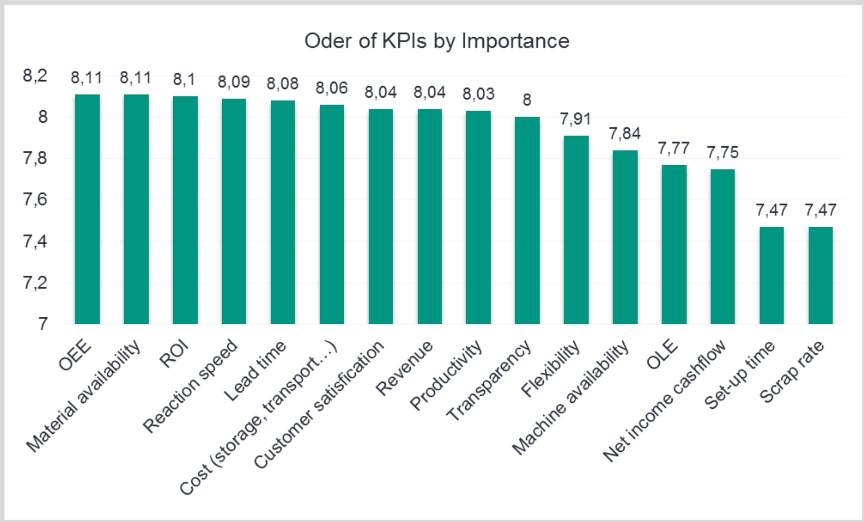


Figure 4-13: Ranking of KPIs by importance (A_Yu 2018)

Selection of KPIs

Since 16 KPIs have are related to each other, it is necessary to generate the categories of KPIs as the representative. Therefore, KPI categories have been introduced (see Figure 4-14). The Quality, Cost and Delivery (QCD) performance metrics model is patterned in the process evaluation of the assembly system (Fujimoto 1999). *Quality* which includes customer satisfaction issues and product/process quality; *cost*, which includes all costs, such as administrative expenses, manufacturing costs, and productivity issues; *delivery*, which includes manufacturing product commitments and delivery of products to the customer. *Availability*, as the fourth category, is emphasized, since it is one of the most important key figures and illustrates ratio of available time for production. Availability could benefit the overall production performance and increase the competitiveness of a factory. The last category, *others*, will not be focused on for further interdependency analysis with location factors and smart automation technologies, since they are either representative by former four categories (e.g. OEE can be representative by metrics from quality, cost and availability. *Flexibility* and *transparency* can be indirectly illustrated by quality, cost and delivery.) or closely associated with financial aspects rather than assembly systems (e.g., revenue), or indicators that are too comprehensive, such as flexibility and transparence.

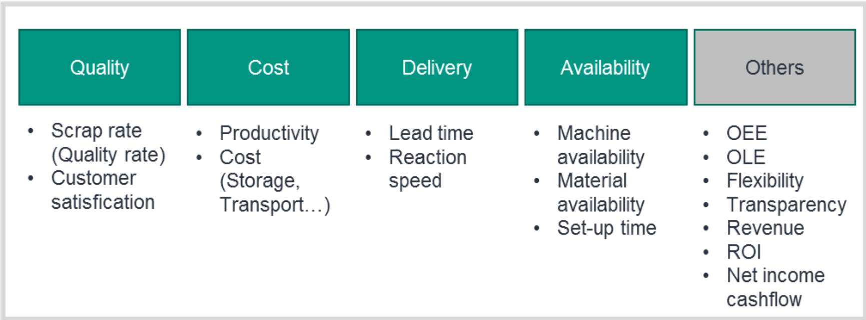


Figure 4-14: The categories of KPIs

The four categories of KPIs have been selected to form the catalog of KPIs. The individual KPI has been defined as single metrics, which belongs to different categories. For active control of each individual KPI, the specific process data have been proposed, which can be collected along the value stream analysis of assembly and actively evaluate the progress. The KPIs structure was created based on these three levels (see Figure 4-15). It is also the basis for analysis of interdependencies among smart automation technologies and KPIs in next section, since the technologies are able to directly influence the process data and then the impact can be transferred to KPIs via process data.

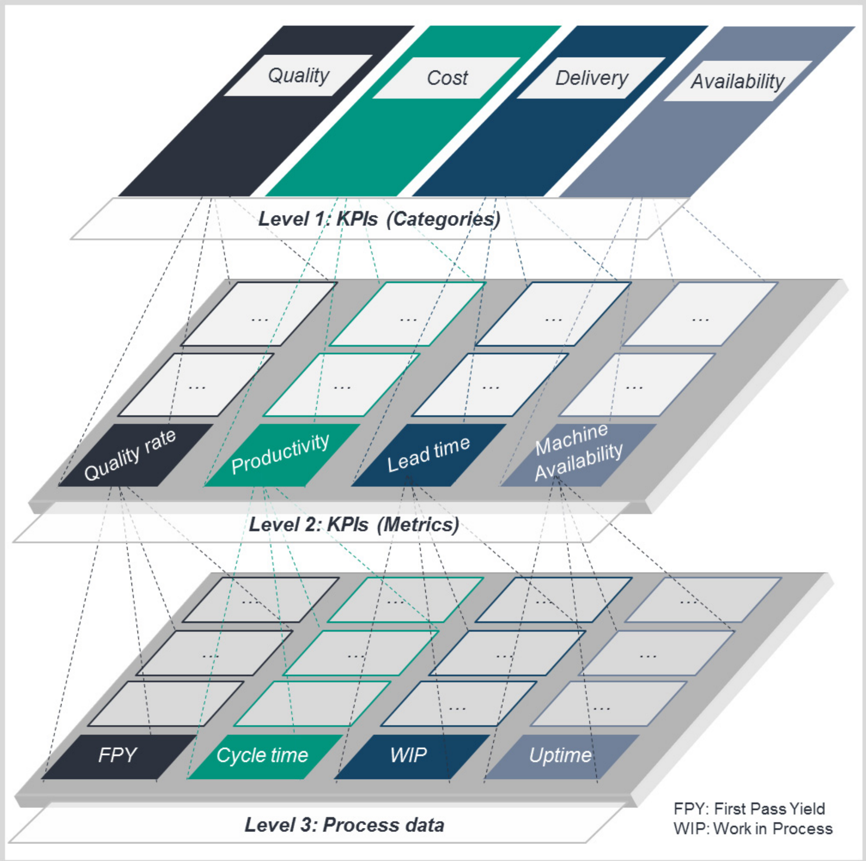


Figure 4-15: Derived KPIs structure based on KPIs Categories

Summary

After the investigation through literature review, questionnaire, data analytics and expert interview, the catalogs of location factors, smart automation technologies and KPIs have been identified for China, as a specific highly dynamic emerging country. The integrated Catalogs are summarized as below (see Figure 4-16)

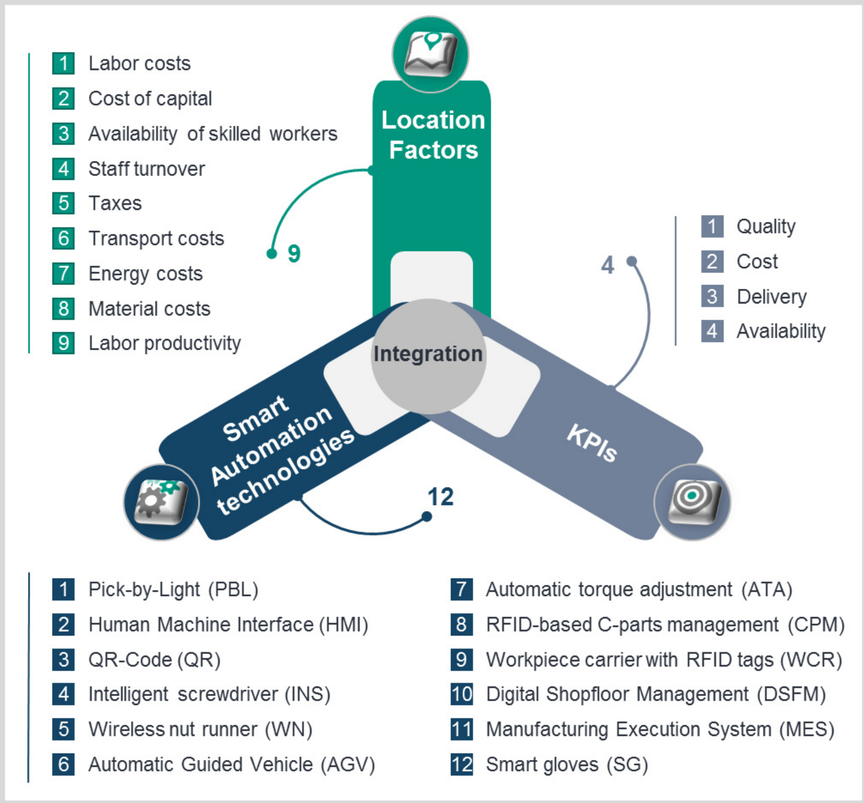


Figure 4-16: Integration of identified catalogs of influence factors

4.3 Interdependency Analysis

4.3.1 Typology of Assembly System Profile

The company profile needs to be defined before the identification of interdependencies between location factors and enabling technologies. Each company has its own characteristics that impact the intensity of interdependencies among location factors and enabling technologies in the field of smart automation as well as key performance indicators.

Company profiles were identified by considering basic information, process factors, and current status. Basic information consists of company type, annual turnover, number of employees, and other similar variables. Process factors include variables related to products or production, such as the complexity of products, delivery time requirements, employee qualifications, the degree of automation, and maintenance costs. Company status information, such as the company's Wi-Fi status or OEE status, is also included as current status (see Figure 4-17).

As an example, type 3 companies are foreign-owned firms with an annual turnover of between ¥40 million and ¥200 million and between 300 and 1,000 employees. For these companies, delivery time requirements range from 30 to 60 days. These companies mainly engage in multi-part production with complex structures. The degree of automation in these companies is high because most tasks are carried out automatically and only a few need to be completed manually. Fifty to seventy percent of each company is covered by Wi-Fi, and their OEE indexes are between 55% and 70%.

The three different types of companies shown in Figure 4-17 are only exemplary of the typology of company profiles. The structure, consisting of aspects and combinations of them could be changed and extended for more precise research or more general application. This work focuses on type 3, as foreign-owned companies in China usually face more challenges related to location factors than other types (Froese & Sutherland et al. 2019). To narrow the scope of foreign owned companies, ones with similar process factors and current status will be taken into consideration. Thus, the following investigation of qualitative and quantitative interdependencies among location factors, smart automation technologies and KPIs is based on the status of type 3 companies.

Taking into consideration the process factors of type 3 companies, corresponding location factors that may affect process factors are selected. For example, if machines execute all of the tasks in a company, labor costs will not have much influence as a location factor. Therefore, this factor will not be selected for analysis. Process factors can also influence the intensity of location factors. Using a similar example, if there is a high degree of automation (process factor) in a company, the influence of labor costs (location factor) will not be very intense.

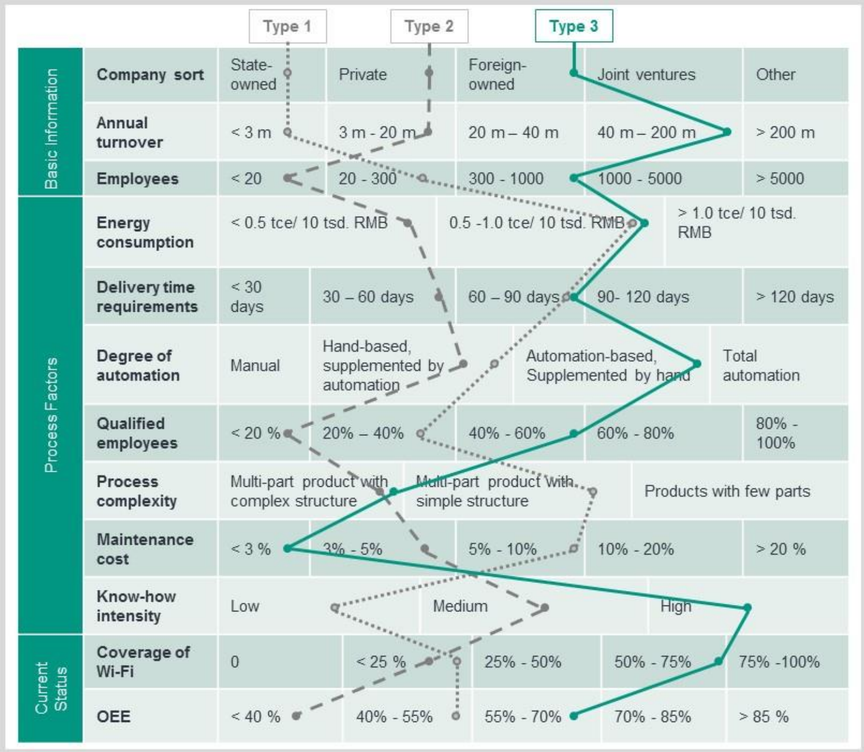


Figure 4-17: Definition of company profile (A_Guo 2019)

Collection of process data with value stream mapping

Value stream mapping (VSM) is a systematic methodology for the development of a value stream oriented company with optimal material and information processes (Molenda & Jugenheimer et al. 2019). Nowadays, it is used across all industry sectors manufacturing companies of various sizes.

Value stream mapping comprises two components that are built on each other. In the first step, the value stream analysis records the current state, and in the second step, the value stream design creates a target-oriented state. In the value stream analysis, one of important steps is to map the sequence of the main processes and fill out data boxes, which consist of the process data such as cycle time, process time, change over time, utilization, number of direct labor, lot size, shift model, scrap etc. (Barring & Nafors et al. 2017). Since the process data are important for measuring selected KPIs according to Figure 4-15, the value stream analysis is applied to collect the process data of assembly line of testbed.

The testbed at the GAMI, which consists of assembly line and provides the demonstration environment for smart automation technologies, was used to do the experiments for the interdependency analysis, especially between smart automation technologies and KPIs. By considering this context, the simplified value stream analysis for the assembly line of the testbed was carried out (see Figure 4-18), which focuses on the collection of process data.

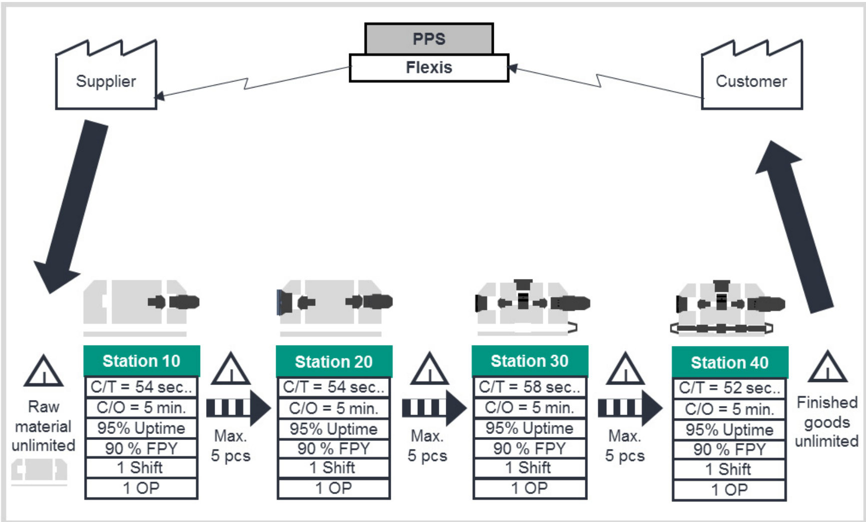


Figure 4-18: Exemplary value stream analysis for assembly line of testbed

4.3.2 Interdependency of Location Factors and Smart Automation

Applying new technologies can achieve improvement of performance in factories, but there are several barriers. (Borhani 2016). After the investigation based on the literature review, four major aspects were clustered to provide a basic understanding for analyzing interdependency between location factors and smart automation technologies. These aspects include resistance to change among employees, economic conditions, training needs, and perception of the usefulness of technologies (see Figure 4-19)

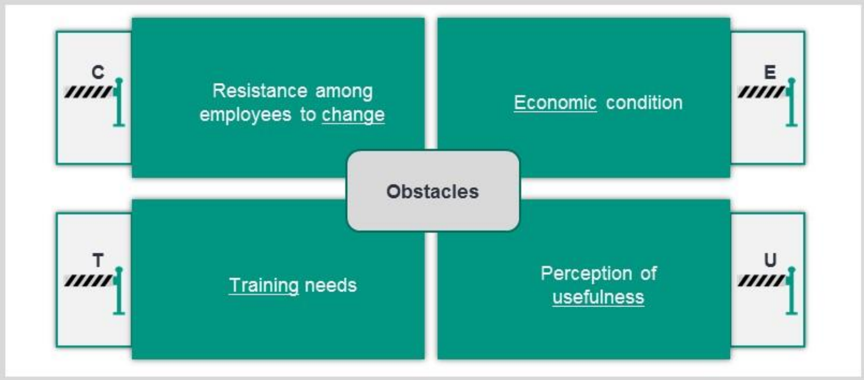


Figure 4-19: Obstacles of location factors to adopting smart automation technologies

First of all, industry is conservative and reluctant to change. As a result, applying new technologies may result in resistance from employees since they must change their ways of working and their workloads may increase. This view was echoed in the expert interviews. Generally, the higher productivity already is, the less a factory or employees will want to change. As a result of resistance to new technologies, benefits may not be achieved, and some factories may even decide to end their efforts to implement new technologies[1].

Secondly, the economic conditions of companies are important to consider since companies must make investments in new technologies. If a new technology is too expensive, some firms, particularly small and medium sized ones, must carefully consider the advantages of applying this kind of technology, as the expense comprises a greater risk. If the benefits may not outweigh the investment, or if the effectiveness of the technology cannot be proven, companies will not adopt the technology (Jacobsson & Linderoth 2010).

Subsequently, the usefulness of the technology must also be considered, and can be measured in percentage points. (Borhani 2016).

Lastly, training needs may also affect the adoption of new technologies. If employees are willing to use a new technology but are not qualified to do so, they cannot successfully achieve benefits. In addition, if a new technology requires training, some employees may be unwilling to accept it, because their workload may increase. Training needs also increase the economic burden of technology for a company (Borhani 2016).

[1]Friedman, E. (2015), "Wearable Technology by Industry Series. Vol. 5–Construction". EnterpriseWear Blog, 18. https://www.brainxchange.com/blog/wearable-technology-by-industry-construction [28.01.2019].

Location factors affect the adoption of enabling technologies when considering the process factors and the above motioned four obstacles. Consequently, the qualitative interdependencies will be identified. For instance, the adoption of a manufacturing execution system (MES) requires qualified employees, and the availability of skilled workers (a location factor) can determine how easy it is to meet this requirement. If the availability of skilled workers is high, the obstacle of meeting training needs is easier to overcome. As a result, the availability of skilled workers has a positive effect on the adoption of MES.

Qualitative Analysis

Taking the initial background as the basis, the interdependency between location factors and smart automation technologies in type 3 companies can be analyzed via expert interviews, of which three in total were conducted. Experts with comprehensive industrial backgrounds from the main technology providers (Rexroth, Werma, Würth) were chosen. Given the profiles of the sample plant (see Figure 4-20) and smart automation technologies as basics, experts were requested to answer the question "How will implementation be affected by location factors for each smart automation technology?" based on the sample plant.

Location Factors		Indicator & Unit	Level 1	Level 2	Level 3
1	Labor Costs	Average annual wage [RMB]	< 60,000	60,000 – 100,000	> 100,000
2	Cost of Capital	Weighted financing cost [%]	< 6 %	6% - 6.5%	> 6.5%
3	Availability of Skilled Workers		low	medium	High
4	Staff Turnover	Staff turnover [%]	< 10 %	10% - 20%	> 20 %
5	Taxes	Total tax/ Turnover [%]	< 5 %	5% - 7%	> 7 %
6	Transport Costs	Transport cost/ Turnover [%]	< 3 %	3% - 10%	> 10 %
7	Energy Costs	10kV electricity price [RMB/kWh]	< 0.50	0.50 – 0.65	> 0.65
8	Material Costs	Regional raw material cost [bn.RMB]	< 500	500 – 1,000	> 1,000
9	Labor Productivitiy		low	medium	high

Sample plant

Figure 4-20: Location factors of sample plant

In this work, the ordinal scale of measurement is applied to present the qualitative interdependency. There are three categories, respectively neutral, positive and negative, the corresponding meaning is introduced in Table 4.8.

Table 4-8: Elements of ordinal scale

Category	Symbol	Meaning
Neutral	/	Location factors have no influence on smart automation technology
Positive	+	Location factors have a positive influence on smart automation technology
Negative	-	Location factors have a negative influence on smart automation technology

Take, for example, the influence of labor costs, cost of capital and availability of skilled workers on the technology Pick-by-Light as shown in Figure 4-21. It indicates that labor costs with level 3 does not have significant influence on the implementation of Pick-by-Light, cost of capital with level 2 has a negative impact, and availability of skilled workers with level 3 has a positive impact.

		Vertical to Horizontal	B: Comparable Matrix - Enabling Technology ↓											
			T1	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**	**T8**	**T9**	**T10**	**T11**	**T12**
No.	**Ab.**	**Location Factors ↓**	PBL	HMI	QR	INS	WN	AGV	ATA	CPM	WCR	DSFM	MES	SG
1	**L1**	Labor costs	/	……	……	……	……	……	……	……	……	……	……	……
2	**L2**	Cost of capital	-	……	……	……	……	……	……	……	……	……	……	……
3	**L3**	Availability of skilled workers	+	……	……	……	……	……	……	……	……	……	……	……
4	**L4**	Staff turnover	……	……	……	……	……	……	……	……	……	……	……	……
5	**L5**	Taxes	……	……	……	……	……	……	……	……	……	……	……	……
6	**L6**	Transport costs	……	……	……	……	……	……	……	……	……	……	……	……
7	**L7**	Energy costs	……	……	……	……	……	……	……	……	……	……	……	……
8	**L8**	Material costs	……	……	……	……	……	……	……	……	……	……	……	……
9	**L9**	Labor productivity	……	……	……	……	……	……	……	……	……	……	……	……

"Vertical to Horizontal" means "Location Factors impacts Smart Automation technologies" in this Figure.
T1 Pick-by-Light - **PBL**, T2 Human Machine Interface - **HMI**, T3 QR-code - **QR**, T4 Intelligent screwdriver - **INS**, T5 Wireless nut runner - **WN**, T6 Automatic Guided Vehicle - **AGV**, T7 Automatic torque adjustment - **ATA**, T8 RFID based C-parts management - **CPM**, T9 Workpiece carrier with RFID tags - **WCR**, T10 Digital Shopfloor Management - **DSFM**, T11 Manufacturing Execution System - **MES**, T12 Smart gloves - **SG**

Figure 4-21: Example of qualitative interdependency location factors to smart automation technologies

Quantitative Analysis

Based on qualitative analysis, the quantitative analysis is derived to be numerical. According to the comments of experts, neutral, positive and negative are respectively equal to 1.0, 1.1 and 0.9. The location factors and smart automation technologies metrics can be expressed as $a_{i,j}(n)$, where i represents for row number, j for column number and n for each expert.

$$a_{i,j}(n), \qquad \text{with } 1 \leq i \leq 9, \quad 1 \leq j \leq 12, n = 1, 2, 3$$

Three interviews results can be consequently be merged into the final matrix. The values of the final matrix $A_{i,j}$ are the arithmetic average of corresponding values from expert interviews as Formula 4.2 shows.

$$A_{i,j} = \frac{\sum_{n=1}^{3} a_{i,j}(n)}{\sum_{n=1}^{3} z_{i,j}(n)}, \qquad \text{with } z_{i,j}(n) = \begin{cases} 1, & a_{i,j}(n) \neq 0 \\ 0, & a_{i,j}(n) = 0 \end{cases} \qquad \text{Formula 4.2}$$

According to the above stated procedure, the answers from three expert interviews were collected (Figure 4-22 (a), (b) and (c)). Since the third expert could only provide information for part of the technologies, the unmentioned ones are displayed with number zero (Figure 4-22 (c)).

B: Comparable Matrix - Enabling Technology ↓

No.	Ab.	Vertical to Horizontal / Location Factors ↓	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
			PBL	HMI	QR	INS	WN	AGV	ATA	CPM	WCR	DSFM	MES	SG
1	L1	Labor costs	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
2	L2	Cost of capital	1,00	0,90	1,00	0,90	0,90	0,90	0,90	1,00	1,00	1,00	0,90	0,90
3	L3	Availability of skilled workers	1,10	1,10	1,00	1,10	1,10	1,10	1,10	1,10	1,00	1,10	1,10	1,10
4	L4	Staff turnover	1,10	1,10	1,00	1,00	1,10	1,00	1,00	1,00	1,00	1,10	1,00	1,10
5	L5	Taxes	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
6	L6	Transport costs	1,00	1,00	1,10	1,00	1,00	1,00	1,00	1,10	1,10	1,10	1,00	1,00
7	L7	Energy costs	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
8	L8	Material costs	1,10	1,10	1,10	1,10	1,10	1,10	1,10	1,10	1,10	1,10	1,10	1,10
9	L9	Labor productivity	1,10	1,10	1,00	1,10	1,10	1,00	1,10	1,00	1,00	1,10	1,10	1,10

(a) Location Factors and Smart Automation technologies – expert review result 1

B: Comparable Matrix - Enabling Technology ↓

No.	Ab.	Vertical to Horizontal / Location Factors ↓	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
			PBL	HMI	QR	INS	WN	AGV	ATA	CPM	WCR	DSFM	MES	SG
1	L1	Labor costs	1,00	1,00	1,10	1,00	1,10	1,10	1,00	1,10	1,10	1,10	1,10	1,00
2	L2	Cost of capital	0,90	1,00	1,00	0,90	0,90	1,00	0,90	0,90	1,00	1,00	0,90	1,00
3	L3	Availability of skilled workers	1,00	1,10	1,00	1,10	1,10	1,00	1,10	1,10	1,00	1,10	1,10	1,10
4	L4	Staff turnover	1,10	1,10	1,00	0,90	1,00	0,90	0,90	1,00	1,00	1,00	1,00	1,10
5	L5	Taxes	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
6	L6	Transport costs	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,10	1,00	1,10	1,10	1,00
7	L7	Energy costs	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
8	L8	Material costs	1,10	1,00	1,10	1,10	1,00	1,10	1,10	1,00	1,10	1,10	1,10	1,00
9	L9	Labor productivity	1,00	1,10	1,00	1,10	1,00	1,00	1,00	1,00	1,00	1,10	1,10	1,00

(b) Location Factors and Smart Automation technologies – expert review result 2

B: Comparable Matrix - Enabling Technology ↓

No.	Ab.	Vertical to Horizontal / Location Factors ↓	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
			PBL	HMI	QR	INS	WN	AGV	ATA	CPM	WCR	DSFM	MES	SG
1	L1	Labor costs	0,00	0,00	1,00	0,00	0,00	1,10	0,00	0,00	1,00	1,10	1,10	0,00
2	L2	Cost of capital	0,00	0,00	1,00	0,00	0,00	1,00	0,00	0,00	1,00	1,00	0,90	0,00
3	L3	Availability of skilled workers	0,00	0,00	1,10	0,00	0,00	1,00	0,00	0,00	1,10	1,00	1,00	0,00
4	L4	Staff turnover	0,00	0,00	1,00	0,00	0,00	1,00	0,00	0,00	1,00	1,10	1,10	0,00
5	L5	Taxes	0,00	0,00	1,00	0,00	0,00	1,00	0,00	0,00	1,00	1,00	1,00	0,00
6	L6	Transport costs	0,00	0,00	1,10	0,00	0,00	1,00	0,00	0,00	1,00	1,10	1,00	0,00
7	L7	Energy costs	0,00	0,00	1,00	0,00	0,00	1,00	0,00	0,00	1,00	1,00	1,00	0,00
8	L8	Material costs	0,00	0,00	1,10	0,00	0,00	1,10	0,00	0,00	1,10	1,00	1,00	0,00
9	L9	Labor productivity	0,00	0,00	1,00	0,00	0,00	1,00	0,00	0,00	1,00	1,10	1,10	0,00

(c) Location Factors and Smart Automation technologies – expert review result 3

Remarks: 1.0=Neutral, 1.1=Positive correlation, 0,9=Negative correlation.
The yellow marked abbreviation of Location Factors means that the Location Factors have no significant impact on the Smart Automation technologies according to expert.
The yellow marked abbreviation of Smart Automation technologies means that the expert gave only answers on these Smart Automation technologies.

Figure 4-22: Summary of expert interview (A_Guo 2019)

According to the expert suggestions, two location factors have no considerable impact on the implementation of the listed smart automation technologies in practice: taxes and energy costs (marked with yellow as shown below). According to Formula 4.2, the final interdependency matrix of location factors and smart automation technologies were generated (see Figure 4-23). Values in the matrix shown in Figure 4-23 indicate the intensity of interdependencies. Greater ones are depicted by higher values, signifying a stronger positive correlation. Conversely, if it is less than one, a lower value shows a stronger negative correlation.

		Vertical to Horizontal	B: Comparable Matrix - Enabling Technology ↓											
			T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
No.	Ab.	Location Factors ↓	PBL	HMI	QR	INS	WN	AGV	ATA	CPM	WCR	DSFM	MES	SG
1	L1	Labor costs	1,00	1,00	1,03	1,00	1,05	1,07	1,00	1,05	1,03	1,07	1,07	1,00
2	L2	Cost of capital	0,95	0,95	1,00	0,90	0,90	0,97	0,90	0,95	1,00	1,00	0,90	0,95
3	L3	Availability of skilled workers	1,05	1,10	1,03	1,10	1,10	1,03	1,10	1,10	1,03	1,07	1,07	1,10
4	L4	Staff turnover	1,10	1,10	1,00	0,95	1,05	0,97	0,95	1,00	1,00	1,07	1,03	1,10
5	L5	Taxes	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
6	L6	Transport costs	1,00	1,00	1,07	1,00	1,00	1,00	1,00	1,10	1,03	1,10	1,03	1,00
7	L7	Energy costs	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
8	L8	Material costs	1,10	1,05	1,10	1,10	1,05	1,10	1,10	1,05	1,10	1,07	1,07	1,05
9	L9	Labor productivity	1,05	1,10	1,00	1,10	1,05	1,00	1,05	1,00	1,00	1,10	1,10	1,05
		Comprehensive Influence to Smart Automation Technology	1,27	1,33	1,25	1,14	1,20	1,13	1,09	1,27	1,21	1,57	1,28	1,27

1.0=Neutral, 1.1=Positive correlation, 0,9=Negative correlation.
The yellow marked abbreviation of Location Factors means that the Location Factors have no significant impact on the Smart Automation technologies according to expert
Comprehensive influence means multiply the given influence number
T1 Pick-by-Light - PBL, T2 Human Machine Interface - HMI, T3 QR-code - QR, T4 Intelligent screwdriver - INS, T5 Wireless nut runner - WN, T6 Automatic Guided Vehicle - AGV, T7 Automatic torque adjustment - ATA, T8 RFID based C-parts management - CPM, T9 Workpiece carrier with RFID tags - WCR, T10 Digital Shopfloor Management - DSFM, T11 Manufacturing Execution System - MES, T12 Smart gloves - SG

Figure 4-23: Location factors and smart automation technologies – summary of expert interview

With high local labor costs, implementing smart automation technologies would be more effective, as it can reduce the number of employees and increase productivity, such as Wireless nut runner (WN), Automatic Guided Vehicle (AGV), RFID-based C-parts management (CPM), Digital Shopfloor Management (DSFM) and Manufacturing Execution System (MES). Therefore, labor costs have a positive impact on these technologies. A medium level of cost of capital can already have negative correlations with technologies requiring relatively high investment, such as Intelligent screwdriver (INS), Wireless nut runner (WN), and Manufacturing Execution System (MES). A high availability of skilled workers can positively influence all the smart automation technologies, as the more high-qualified employees there are, the lower the training cost investment and the better effectiveness by applying technologies will be. Technologies that help by increasing operation reliability and by reducing invested training costs show more significant effectiveness when the local staff turnover is high, thus, they are positively related to it. Transport cost has a positive impact on technologies such as QR-Code (QR), RFID-based C-parts management (CPM) and Digital Shopfloor Management (DSFM), which support for a more efficient and reliable inventory and logistics management and therefore can be adopted to balance the relatively high transport costs. With a high level of material costs, companies will expect to apply new technologies to reduce defect ratio, ensure production quality and trace important components to reduce total material costs. Consequently, material costs have a positive influence on smart automation technologies. High labor productivity from qualified workers can further amplify the effectiveness of implementing the technologies and, as a result, it has positive impact on them. Although two location factors have no considerable impact at the present, these factors are still listed as possible variables by considering future uncertain situation.

4.3.3 Interdependency of different smart automation technologies

Smart automation technologies have also a significant influence on each other. Some basic technologies, for example, must be implemented as precondition before some others can work, and some technologies can be applied at the same time for greater improvement. This section presents the approach to derive an interrelation matrix of smart automation technologies through expert interviews.

Expert interviews

Firstly, four types of interdependencies between different technologies and initial corresponding factor parameters were defined as shown in Table 4.9.

Table 4-9: The overview types of interdependencies among smart automation technologies

Type	Parameter	Mark color
Precondition	1.00	Marked with yellow
Strong support	0.75	Marked with green
Weak support	0.25	Marked with light green
Neutral	0.00	White

Three expert interviews were conducted in total, which is similar to the previous procedure. The experts were requested to answer the question regarding each technology “How can this technology influence the implementation of other technologies such as precondition, providing strong or weak support, or independent?”. Answers were then filled into the interrelation matrix (see Figure 4-24 as an example).

		Vertical to Horizontal	B: Comparable Matrix - Enabling Technology ↓											
			T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
No.	Ab.	Enabling Technology ↓	PBL	HMI	QR	INS	WN	AGV	ATA	CPM	WCR	DSFM	MES	SG
1	T1	Pick-by-Light (PBL)								0,00				
2	T2	Human Machine Interface (HMI)								0,25				
3	T3	QR-Code (QR)								0,00				
4	T4	Intelligent screwdriver (INS)								0,00				
5	T5	Wireless nut runner (WN)								0,00				
6	T6	Automatic Guided Vehicle (AGV)								0,75				
7	T7	Automatic torque adjustment (ATA)								0,00				
8	T8	RFID-based C-Parts management (CPM)												
9	T9	Workpiece carrier with RFID tags (WCR)								1,00				
10	T10	Digital Shopfloor Management (DSFM)								0,00				
11	T11	Manufacturing Execution System (MES)								0,75				
12	T12	Smart gloves (SG)								0,00				

Figure 4-24: Example of interrelation matrix of smart automation technologies

In Figure 4-24, the column of T8 RFID-based C-Parts management (CPM) has been taken as an example. Since CPM is primarily based on Workpiece carrier with RFID tags (WCR) technology, WCR is seen as a precondition for CPM. With the strong support from Automatic Guided Vehicle (AGV) and Manufacturing Execution System (MES), CPM could enhance its benefits for the production significantly. In addition, QR-Code (QR) can also provide weak support for CPM, meanwhile other technologies without obvious impact on CPM are marked with 0.

Elements of the interrelation matrix can be expressed as $b_{i,j}(n)$, where i represents for row number, j for column number and n for each expert:

$$b_{i,j}(n), \text{with } 1 \le \ i \le 12, 1 \le j \le 12, n = 1, 2, 3$$

Subsequently, data by each expert interview can be merged into the final matrix. If a precondition relationship has been stated at least once, the corresponding value of the final matrix $B_{i,j} = 1$, otherwise $B_{i,j}$ is the arithmetic average of corresponding values from expert interviews, namely:

$$B_{i,j} = \begin{cases} 1, & \mid \exists n \in \{1,2,3\}: b_{i,j} = 1 \\ \dfrac{\sum_{n=1}^{3} b_{i,j}(n)}{\sum_{n=1}^{3} z_{i,j}(n)}, & \mid \forall n \in \{1,2,3\}: b_{i,j} \neq 1, z_{i,j}(n) = \begin{cases} 1, b_{i,j}(n) \neq blank \\ 0, b_{i,j}(n) = blank \end{cases} \end{cases} \qquad \text{Formula 4.3}$$

As the above procedure introduced, answers from three expert interviews were collected (see Appendix A7). According to Formula 4.3, the correlation between different smart automation technologies can be seen in Figure 4-25.

		Vertical to Horizontal	B: Comparable Matrix - Enabling Technology ↓											
			T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
No.	Ab.	Enabling Technology ↓	PBL	HMI	QR	INS	WN	AGV	ATA	CPM	WCR	DSFM	MES	SG
1	T1	Pick-by-Light (PBL)		0,13	0,00	0,13	0,13	0,13	0,00	0,00	0,00	0,42	0,42	0,38
2	T2	Human Machine Interface (HMI)	0,13		0,00	0,38	0,38	0,13	0,00	0,00	0,00	0,42	0,50	0,75
3	T3	QR-Code (QR)	0,17	1,00		1,00	1,00	0,25	1,00	0,17	0,17	0,58	0,58	0,08
4	T4	Intelligent screwdriver (INS)	0,00	0,00	0,00		0,13	0,00	0,38	0,00	0,00	0,33	0,42	0,00
5	T5	Wireless nut runner (WN)	0,00	0,00	0,00	0,13		0,00	0,00	0,00	0,00	0,42	0,33	0,00
6	T6	Automatic Guided Vehicle (AGV)	0,00	0,00	0,00	0,00	0,00		0,00	0,50	0,00	0,42	0,75	0,00
7	T7	Automatic torque adjustment (ATA)	0,00	0,00	0,00	0,50	1,00	0,00		0,00	0,00	0,33	0,33	0,00
8	T8	RFID-based C-Parts management (CPM)	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,58	0,58	0,00
9	T9	Workpiece carrier with RFID tags (WCR)	0,17	1,00	0,17	1,00	0,50	0,42	1,00	1,00		0,58	0,58	0,08
10	T10	Digital Shopfloor Management (DSFM)	0,33	0,25	0,33	0,25	0,33	0,33	0,00	0,25	0,08		0,00	0,00
11	T11	Manufacturing Execution System (MES)	0,58	0,75	0,33	0,42	0,33	0,75	0,17	0,50	0,08	1,00		0,00
12	T12	Smart gloves (SG)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,08	0,00	

Figure 4-25: Interdependency between different smart automation technologies (A_Guo 2019)

QR-Code (QR) and Workpiece carrier with RFID tags (WCR) act as important basic technologies and enable the problem-free operation of some other technologies such as Human Machine Interface (HMI), Intelligent screwdriver (INS), Wireless nut runner (WN), Automatic torque adjustment (ATA) and RFID-based C-Parts management

(CPM). Since Automatic torque adjustment (ATA) is regarded as a key function of Intelligent screwdriver (INS) and Wireless nut runner (WN), it is a precondition for both. Digital shopfloor management (DSFM) is nowadays usually applied together with other big systems such as Customer Relationship Management, Enterprise Resource Planning, and Manufacturing Execution System (MES). Since MES could provide the reliable data of production execution, it is considered as a precondition for Digital shopfloor management (DSFM). The technologies can be successfully applied only if the precondition technologies have been fully implemented.

Noticeably, Digital shopfloor management (DSFM) and Manufacturing Execution System (MES) as integrated and systematic technologies can be supported by almost all other technologies which are connected to them through information flow, especially strongly by Pick-by-light (PBL), Human Machine Interface (HMI), QR-Code (QR), Automatic Guided Vehicle (AGV) and RFID-based C-Parts management (CPM), and vice versa. Production data generated or collected by these technologies can be transmitted to the two systems and used for further analysis and decision-making to improve the production performance. In return, the two systems also strengthen the effectiveness and reliability of these technologies. QR and RFID as basic technologies provide support for all other technologies. By transporting materials around on the shopfloor or in a warehouse, Automatic Guided Vehicle (AGV) improves the efficiency of intralogistics, which provides a strong support for RFID-based C-Parts management (CPM) by increasing the speed of transporting empty C-part bins. Human Machine Interface (HMI) assists the workers to operate correctly and quickly in a more efficient way compared to paper-based instructions. This can help the Smart gloves (SG) to collect more valid motion and operation data for further analysis, which is especially beneficial in training cases.

More important rules emerged when the experts reviewed the generated results. First, that the technology could not be both the precondition and support for the studied technology at the same time. The precondition has a higher priority than the support. Second, the numeral results are initially used for qualitative analysis. They should be transformed according to the feasibility scale for the calculation of practical influences. Here the ratio 3 to 1 was recommend by experts, therefore, the numerical result of matrix in Figure 4-25 has been adjusted (see Figure 4-26). For instance, the support impact from Pick-by-Light (PBL) to Human Machine Interface (HMI) has been adjusted by round up to 4% (0.13 is divided by ratio 3). Third, the cumulative support influence should be normally maximum 25%, while it can be maximum 35% for MES and DSFM. Last the efforts of implementing the technologies is standardized based on number of days (see Table 4-10).

Table 4-10: Base effort for the implementation of the technologies without influence of location factors by expert suggestions

No.	Smart Automation technologies	Efforts (days)	No.	Smart Automation technologies	Efforts (days)	No.	Smart Automation technologies	Efforts (days)
T1	PBL	30	T5	WN	84	T9	WCR	78
T2	HMI	144	T6	AGV	264	T10	DSFM	360
T3	QR	108	T7	ATA	252	T11	MES	288
T4	INS	240	T8	CPM	96	T12	SG	86

Based on the modification of expert reviews, the quantitative interdependencies for smart automation was updated as follows (see Figure 4-26).

		Vertical to Horizontal	B: Comparable Matrix - Enabling Technology ↓											
			T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
No.	Ab.	Enabling Technology ↓	PBL	HMI	QR	INS	WN	AGV	ATA	CPM	WCR	DSFM	MES	SG
1	T1	Pick-by-Light (PBL)		4%		4%	4%	4%				14%	14%	13%
2	T2	Human Machine Interface (HMI)	4%			13%	13%	4%				14%	17%	25%
3	T3	QR-Code (QR)	6%	100%		100%	100%	8%	100%	6%	6%	19%	19%	3%
4	T4	Intelligent screwdriver (INS)					4%		13%			11%	14%	
5	T5	Wireless nut runner (WN)				4%						14%	11%	
6	T6	Automatic Guided Vehicle (AGV)								17%		14%	25%	
7	T7	Automatic torque adjustment (ATA)				17%	100%					11%	11%	
8	T8	RFID-based C-Parts management (CPM)										19%	19%	
9	T9	Workpiece carrier with RFID tags (WCR)	6%	100%	6%	100%	17%	14%	100%	100%		19%	19%	3%
10	T10	Digital Shopfloor Management (DSFM)	11%	8%	11%	8%	11%	11%	0%	8%	3%			
11	T11	Manufacturing Execution System (MES)	19%	25%	11%	14%	11%	25%	6%	17%	3%	100%		
12	T12	Smart gloves (SG)										3%		

Figure 4-26: Quantitative interdependency among smart automation technologies

4.3.4 Interdependency between Smart Automation and KPIs

By applying smart automation technologies, the performance of the assembly systems will be improved in different aspects and different degrees, which can be measured and presented by relevant process data. This section states the approach to derive an influence matrix of technologies and production KPIs under experimental conditions in the assembly line of testbed.

As stated in Section 4.2.3, a KPI catalog was generated, in which four categories of production KPIs were defined, Quality, Cost, Delivery and Availability, respectively. Since the KPIs are abstract, the KPI structure has is introduced in Figure 4-15, respectively, the KPIs category could be represented by metrics, and the metrics can be further measured and calculated by process data. On the one hand, the process data can be visualized through the value stream analysis. On the other hand, the improvement of process data causes by smart automation technologies can be measured experimentally in the assembly line of testbed. Thus, an influence matrix between smart automation technologies and process data can be achieved, which can be a bridge between smart automation technologies and KPIs. Additionally, technology providers have been interviewed as a complementary method of gathering process data.

As the first step, the KPIs structure has been extended (see Table 4-11) and visualized in the flow chart (see Figure 4-27) to represent the overview of KPIs, which is carried out based on the literature review and industrial expertise review.

Table 4-11: Extended structure of KPIs

Level	**Structure**	**Name**			
1	KPIs Categories (4)	Quality	Cost	Delivery	Availability
2	Metrics (5)	QR	PROD	LT	AS, POT
3	Process Data (12)	FPY, GQC, SCQ	PQ, NE, CT	WIP	PBT PDT ODT ,LDT, AWUBT,

Remarks: Quality Rate (QR) / First Pass Yield (FPY) / Good Quantity Counted (GQC) / Scrap Quantity (SCQ) / Productivity (PROD) / Produced Quantity (PQ) / Number of Employees (NE) / Cycle Time (CT) / Lead Time (LT) / Work In Process (WIP) / Available System (AS) / Planned Operation Time (POT) / Planned Busy Time (PBT) /Planned Down Time (PDT) / Other Down Time (ODT) / Logistic Delay Time (LDT) / Actual Work Unit Busy Time (AWUBT)

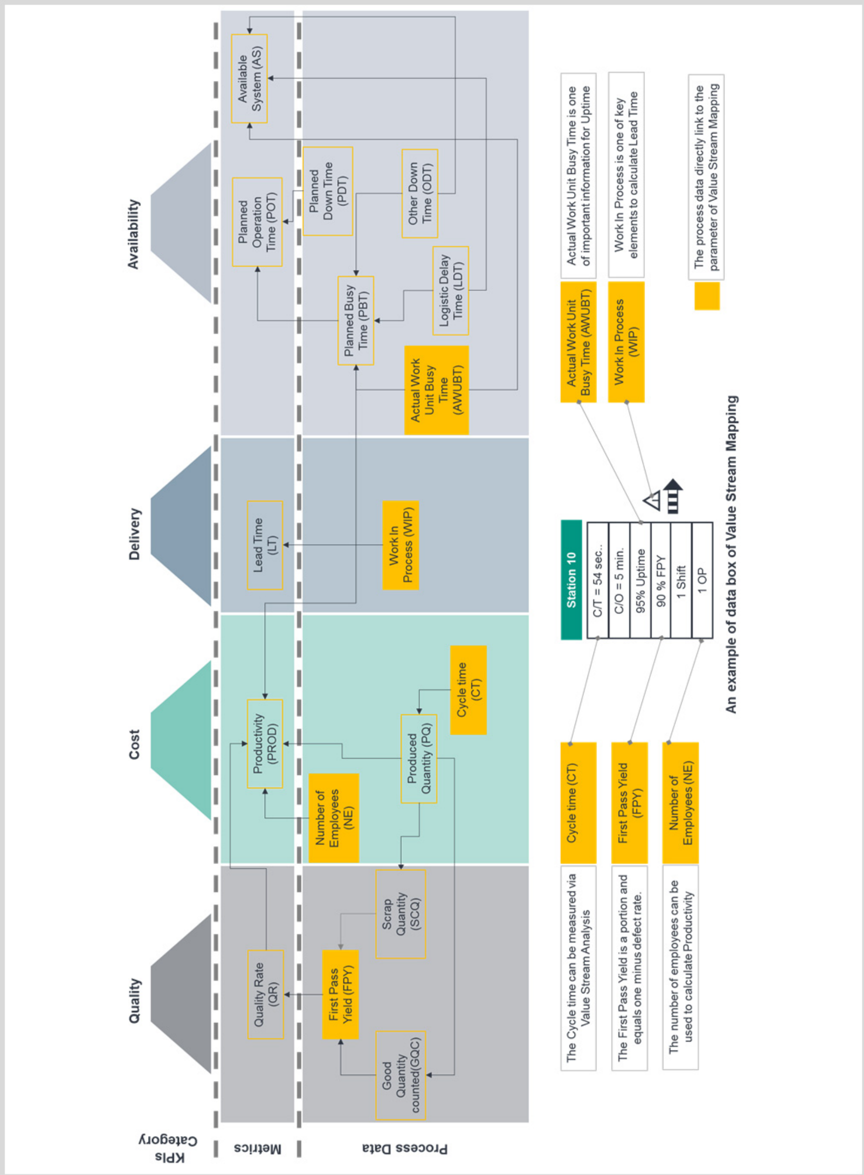


Figure 4-27: KPIs influence flow chart

The relevant KPIs were calculated according to following formulas.

Quality

As representative of quality rate, First Pass Yield (FPY) is defined as portion of manufactured parts that meet quality requirement after just the first run (without being scrapped)

$$v_{FPY} = \frac{n_{GQC}}{n_{GQC} + n_{SCQ}} \times 100\% \qquad \text{Formula 4.4}$$

Where v_{FPY} is the value of First Pass Yield, n_{GQC} is number of produced good parts by first run, when the parts are not allowed to be reworked, namely there are only good parts or scraps. n_{SCQ} is numer of defect parts, namely scrap quantity. Then

$$n_{PQ} = n_{GQC} + n_{SCQ} \qquad \text{Formula 4.5}$$

$$v_{FPY} = 1 - v_{DF} \qquad \text{Formula 4.6}$$

Where n_{PQ} *is produced quantity,* v_{DF} *is defect rate.*

Cost

Productivity describes the relation between number of produced good parts and total labor needed in the considered value stream.

$$v_{PROD} = \frac{n_{GQC}}{t_{AWUBT} \times n_{NE}} \qquad \text{Formula 4.7}$$

Where v_{PROD} is the value of productivity. n_{NE} is number of employees, namely the number of operators in the assembly. If the FPY is assumed as 100%, n_{GQC} equals to n_{PQ}. Then the relation between productivity and cycle time can be described as followed.

$$n_{PQ} = \frac{t_{AWUBT}}{t_{CT}} \qquad \text{Formula 4.8}$$

$$v_{PROD} = \frac{1}{t_{CT} \times n_{NE}} \qquad \text{Formula 4.9}$$

Where t_{CT} is cycle time.

Delivery

Considering the assembly line, the lead time t_{LT} *equals number of Work in Process (WIP) multiplied with cycle time of bottleneck.*

$$t_{LT} = n_{WIP} \times t_{CToB} \qquad \text{Formula 4.10}$$

Where n_{WIP} is number of Work in Process (WIP), t_{CToB} is the cycle time of the bottleneck. When the assembly line is well balanced, the t_{CToB} is same as t_{CT}

Availability

Available system (i.e. machine availability) can be represented by Uptime, which is percent of time that equipment/machines are up and running.

$$v_{UT} = \frac{t_{AWUBT}}{t_{PBT}} \times 100\% \qquad \text{Formula 4.11}$$

$$t_{PBT} = t_{AWUBT} + t_{LDT} + t_{ODT} \qquad \text{Formula 4.12}$$

Where v_{UT} is the machine availability, t_{AWUBT} is actual work unit busy time, t_{PBT} is planned busy time, t_{LDT} is logistic delay time and t_{ODT} is other down time.

In this work, the investigation was conducted through experiments in the assembly system of testbed in Yangtze Delta Zone of China, where the selected twelve technologies are utilized. The reason is that it is difficult to have access to factory sites and their facilities due to risks and safety concerns. Therefore, it was not quite feasible to choose a real factory to implement all smart automation technologies for collection of data. The testbed based experiment has been devised to down-scale and simulate the real instance so that the knowledge gained from experiment can be generalized to advise real practice to a large extent (Hou & Wang et al. 2015). For example, the assembly workstation and their assembly sequencing all came from real data and real drawings provided by industrial partner. As this is a demonstrated environment, certain simplifications have been made. For instance, the influence of the learning curve was not considered in the experiment.

There is a production line for assembly valve slice in testbed. The two rounds design was originally planned in the experiment. One round is conventional assembly without applying investigated smart automation technology, the other round is with application of investigated smart automation technology. 32 valve slices have been assembled for each comparison, namely, 16 valve slices for each round. The process data as critical indicators were recorded, such as cycle time, working time, number of defect parts, number of good parts, and number of work in process (WIP). The experiment was recorded using a video camera.

Examples of experiment processes are shown in Figure 4-28. The corresponding process data were collected and further calculated into final related production KPIs according to Formula 4.4 – 4.12. Then, the change rates of parameters after the application of technologies were analyzed accordingly. As one of examples, the result of Wireless nut runner (WN) is shown in Table 4-12. The rest of results for all twelve technologies are listed in Appendix A8.

a. Experiment of Wireless nut runner (WN) — b. Experiment of Intelligent screwdriver (INS) — c. Experiment of Smart gloves (SG)

Figure 4-28: Examples of experiment processes (A_Guo 2019)

The experiment has quantitatively and qualitatively investigated the interdependencies between smart automation technologies and KPIs in practical way, rather than developing a ready-to-be-applied technologies for industry. The results from the experiment can partially advise the impact of application smart automation technologies in assembly system.

Table 4-12: Result of Wireless nut runner (WN) (A_Guo 2019)

Process data	Unit	Before: Electric Wrench	After: Wireless nut runner	Change Rate
Uptime	%	99.55	99.66	0.1%
FPY	%	87.5	93.75	7%
Cycle Time	s	58.5	53.5	8.5%
WIP	Pcs	1	1	0

Based on these results, not only can the benefits stated in the technology profiles in Section 4.2 be further confirmed and described more precisely, but they also help in the development of a KPI-oriented implementation strategy of technologies. When companies need to improve several specific aspects or KPIs of the production, this matrix can serve as one reference, together with the interdependency matrix between different technologies, for selecting the relevant technologies and to consider the priorities of implementation.

4.3.5 Determination of the Interdependency of Location Factors and KPIs

In different locations, industrial companies may place higher value on different KPIs. For instance, labor productivity may be considered as less important KPI metric in a region where the average automation degree is relatively high. In this section, a priority ranking of KPIs namely Quality, Cost, Delivery and Availability for three main regions in China, namely Peking-Tianjin-Hebei Delta, Yangtze-River Delta and Pearl River Delta, is generated through analysis of questionnaire surveys.

First, based on Appendixes A2 and A6, the KPI metrics have been further analyzed, which are individually sorted by three delta zones (see Table 4-13).

Table 4-13: Importance of KPIs in different regions (A_Yu 2018)

Peking-Tianjin-Hebei Delta		Yangtze-River Delta		Pearl River Delta	
KPI	**Rate***	**KPI**	**Rate***	**KPI**	**Rate***
Material availability	8.25	Cost	8.20	Material availability	8.21
Revenue	8.25	Transparency	8.15	Reaction speed	8.21
OEE	8.15	Lead time	8.13	Productivity	8.16
Productivity	8.15	Reaction speed	8.13	OEE	8.11
Customer satisfaction	8.15	ROI	8.13	Net cashflow	8.11
ROI	8.10	OEE	8.10	Lead time	8.05
Lead time	8.00	Flexibility	8.10	ROI	8.05
Reaction speed	7.90	Customer satisfaction	8.03	Cost	8.00
Cost	7.85	Material availability	8.00	Revenue	8.00
Transparency	7.75	Machine availability	7.95	Transparency	7.95
Machine availability	7.70	Revenue	7.95	Customer satisfaction	7.95
Flexibility	7.55	OLE	7.90	Flexibility	7.89
OLE	7.50	Productivity	7.90	Scrap rate	7.89
Net cashflow	7.40	Net cashflow	7.75	OLE	7.79
Set-up time	6.95	Set-up time	7.68	Machine availability	7.74
Scrap rate	6.65	Scrap rate	7.68	Set-up time	7.58

*Rate is in the scale from 1 to 10, the larger the number, the more the important KPI is.

Secondly, according to Figure 4-14, the KPI metrics can be used to represent the importance of KPI categories. The importance of KPI categories have been estimated by average value of importance of KPIs metrics. For example, Quality consists of scrap rate and customer satisfaction. The value of both of these metrics are respectively 6.65 and 8.15 in Peking-Tianjin-Heibei Delta. Thus, the value of importance of Quality is 7.4. Then the rankings of KPIs for different regions can be derived in Table 4-14 (1=highest, 4=lowest).

The rankings present the interdependency between location factors and KPIs. It could simplify the analysis of implementation strategy in the preliminary phase. The most important several KPIs can be firstly considered for further analysis based on the individual situation.

Table 4-14: Interdependency between location factors and KPIs

KPIs	Peking-Tianjin-Hebei Delta	Yangtze-River Delta	Pearl River Delta
Quality	4	4	3
Cost	1	2	2
Delivery	2	1	1
Availability	3	3	4

4.3.6 Net of Bilateral Interdependencies

Based on the identified interdependencies among location factors and smart automation technologies, smart automation technologies-smart automation technologies, smart automation technologies-KPIs, and location factors-KPIs, the net of bilateral interdependencies can be generated, which is basic knowledge input for modeling and simulation of assembly systems (see Figure 4-29).

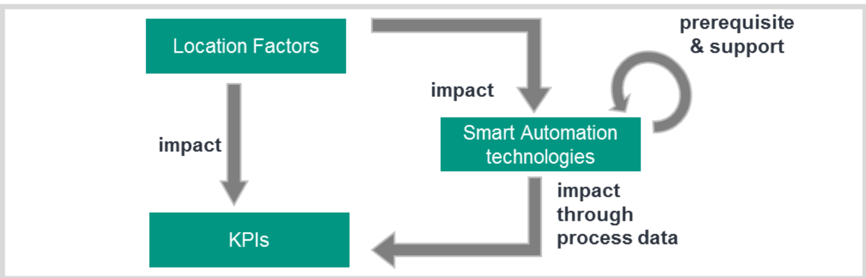


Figure 4-29: Representation for net of bilateral interdependencies

4.4 Modeling and Simulation

The aim of this section is to create the model and simulation of bilateral interdependencies in the assembly system, which is the basis for derivation of the implementation strategy for specific assembly systems in the next section. It consists of three parts. First, the framework conditions and corresponding implications for the model are derived as preparation of model (4.4.1). Subsequently, hybrid modeling is developed for interdependencies within assembly systems, from which the connection to the model is created (4.4.2). In the end, the experiments of simulation are designed accordingly (4.4.3).

4.4.1 Preparation of Model

The aim of this section is to derive framework conditions for the model. For this purpose, the requirements and concepts are first described, from which implications for the model are then derived.

Requirements of model

In the following, requirements relevant to the author's approach are explained. They consist both of the findings drawn in Section 3 on the analysis of the state of the art and of the results of several workshops with industrial experts.

1. **Consideration of all interactions**
   One of the fundamental findings of the literature review in Section 3 is the importance of considering all relevant interactions. One of the most important interactions is the interdependencies of the smart automation technologies with each other. The model must take into account the extent to which technologies are interdependent or support each other. Additionally, the influence of location factors also need to be integrated. It is important to take into account the specific regional circumstances when determining an implementation strategy. In addition, clear KPIs must be defined in order to make decisions efficiently.
2. **Hybrid method modeling**
   The implementation strategy of smart automation technologies is characterized by a holistic approach to assembly systems. This means that not only production-economical, but also strategic elements are considered during technology introduction. Correspondingly, different perspectives such as strategic level (e.g.,

management) and operational level (e.g., engineers) must also be taken into account in a simulation, which can be achieved by combining the more operational DES modeling and the more strategic System Dynamics technique. In addition, it is assumed that the simulation results are not sufficiently trusted by the companies if company specifics are only superficially considered by means of parameters. It is very difficult to quantify company-specific conditions sufficiently precisely using a few variables. Accordingly, operational DES modeling of the actual assembly system is needed.

3. **Sequential technology implementation**
   The model should be kept as simple as possible, so that it can be implemented without a great deal of previous knowledge. The same applies to the simulation results, which must be intuitively comprehensible. Accordingly, it is necessary to clearly limit the complexity. In this work, this is done by considering only sequential technology implementations. This means that technologies are not implemented at the same time, but always one after the other.
4. **Intelligent reduction**
   A sequential implementation has a complexity of n! (i.e. n-faculty = 1*2*3*...*n) different possibilities (März & Krug et al. 2011). n stands for the number of technologies to be implemented. So, if ten technologies are implemented in a company, there are over 3.5 million different sequences. Especially the use of a DES model, which usually requires longer computing times, would make the use of a classic optimization algorithm considerably more difficult. Consequently, a suitable "ranking & selection" approach is needed to limit the various implementation options and to find a solution that comes as close as possible to the optimum.
5. **Variability of the selected technologies**
   The latest smart automation technologies are able to be considered at all times. Accordingly, the model must be structured so that other technologies can be added without major effort. The selection of technologies must also be adapted with regard to this variability and should be made for strategic reasons.
6. **Adaptation of the models for different applications and continuous improvement**
   An important requirement is that the model is continuously developed. Consequently, as many parts of the process model as possible should be standardized to make the improvement process efficient. That means the model should be

structured as much as necessary in sub-models, so that these can be used on other fields. In addition, the data basis should be continuously improved and practical experience should be integrated.

Implications

This section considers the requirements presented above and derives implications. The goal is to develop a framework for the model.

System Dynamics (SD) is especially suitable for strategic considerations of a system. In addition, this modeling technique allows for the easy representation of interactions by means of rates and feedback loops. Discrete-event simulation (DES), in turn, acts much better at the operational level. The representation of a production system and its chains can be best implemented with DES. Accordingly, this division is also suitable for use in this work. With the exception of (Peter 2009), the literature in the section *State of the Art* has concentrated on only one of the two types of modeling and thus has left out important aspects with regard to the question of this work.

One difficulty lies in linking the two modeling techniques. Most interdependencies interact with the technologies, which should therefore be modelled in System Dynamics. It is important that new technologies can be added variably and that the models can be reused for other use cases. These two requirements cannot be met if the technologies are modeled operationally with DES, because otherwise they would have to be strongly integrated into the production system and its interactions. For example, if an AGV is implemented, it is not possible to model itself in the production system. Instead, the effect that an AGV would have is simulated, such as reducing transport time. This creates a clear interface between the two models. In addition, by quantifying the effect, new technologies can be added to the model without much effort. This probably reduces the accuracy of the simulation, but in contrast to Aull (2013) and Liebrecht (2020), the actual production system is still simulated and not simply the effect of the technologies on the key figures is estimated. Correspondingly, a suitable level of accuracy can be assumed with good quantification.

Overall framework of modeling and simulation

The overall framework of modeling and simulation is displayed in Figure 4-30. The timely change of process parameter during the implementation of smart automation technologies and its own support as well as prerequisite will be simulated with the method of System Dynamics. The Discrete Event Simulation will be put into use, in order to simulate the production line of the production system. There should be several workstations in the production line, which should be simulated by means of Agent Based Simulation. Because of the similarity of every single workstation, the modular module represented workstations could be added or removed with drag and drop, so that the reconfiguration and flexibility of the model has been enhanced.

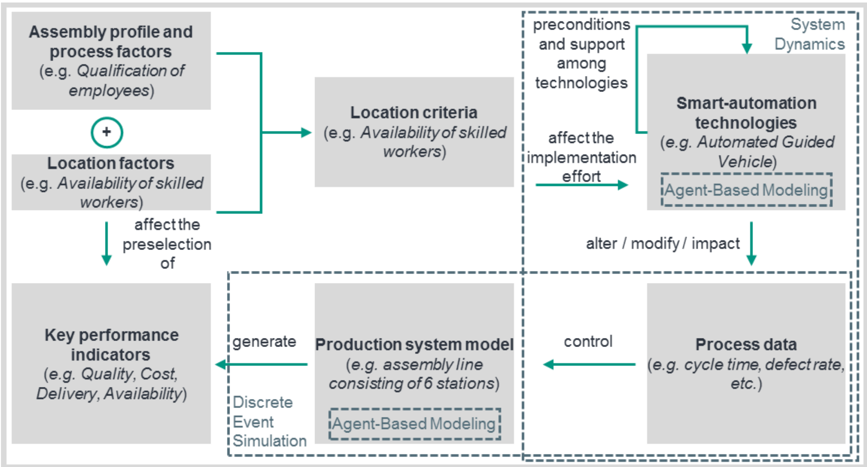


Figure 4-30: Overall framework of modeling and simulation (A_Schrage 2019; A_Ding 2019)

According to the VDI-3633, creating and verifying simulation model needs to be conducted before planning of simulation studies. The modeling of interdependencies with System Dynamics (SD) is first introduced and the modeling of assembly systems is described afterwards. Then, the connection of models is explained followed by the introduction of modeling of KPIs.

4.4.2 Modeling of Interdependencies of the Technologies with System Dynamics

The SD model depicts the technologies and their interdependencies. In the SD model, the technologies and their interactions are mapped. The implementation effort is measured in days and each technology has a number of days for the entire implementation. How much effort must be invested in the implementation of a technology is examined through technology provider (see Table 4.10). In reality, technologies often have an impact on production already during their implementation (Aull 2013). How the effect of a technology relates to its degree of implementation is first considered in the following, before the interdependencies with regard to potential linkages are then analyzed in more detail. Additionally, the initial implementation level of technologies are considered.

Curve of the technology implementation

In reality, the effect of the technologies is not linear with the degree of implementation. Particularly at the beginning of a technology introduction, there are various obstacles that inhibit its effect (see Section 4.3.2). By considering these obstacles, it is possible to illustrate the relationship between implementation and effect using purposeful, deliberate mathematical formulas (Formula 4.13 – 4.15). Formula 4.13 is based on the sigmoid function and corresponds to the previously derived curve.

The curves of the technology implementation are extended to the additionally two curves, which are depicted with linear function and multi slope function. The linear function explains the implementation of a technology based on a timeline. The definition of the multi slope function is that the implementation and effect are with different ratios. It is assumed that for the first 25% of a technology implementation, the curve is with the slope that effect level can be reached to 25%. In the middle 50% of the implementation process, 10% of the effect level is gained. The remaining 65% of the effect level is finished during the last 25% of the implementation. For example, it is assumed that for a technology that needs 100 days to finish the implementation, the effect level reaches 30% while it is on the 50th implementation day, according to multi slope function. The functions of three process curve are as follows:

Sigmoid function:

$$y = \frac{1}{1 + e^{-12\cdot(\frac{t_i}{T_i} - 0.5)}}, \qquad \frac{t_i}{T_i} \in [0, 1] \qquad \text{Formula 4.13}$$

Linear function:

$$y = \frac{t_i}{T_i}, \qquad \frac{t_i}{T_i} \in [0, 1] \qquad \text{Formula 4.14}$$

Multi Slope function:

$$y = \begin{cases} \frac{t_i}{T_i}, & \frac{t_i}{T_i} \in [0, 0.25) \\ 0.25 + 0.2 \cdot (\frac{t_i}{T_i} - 0.25), & \frac{t_i}{T_i} \in [0.25, 0.75) \\ 0.35 + 2.6 \cdot (\frac{t_i}{T_i} - 0.75), & \frac{t_i}{T_i} \in [0.75, 1] \end{cases} \qquad \text{Formula 4.15}$$

Thereinto, t_i stands for the number of days already spent for the technology i and T_i stands for the total days the technology needs to be entirely implemented. y stands for the implementation effect level. The formulas have been visualized through graphs (see Figure 4-31).

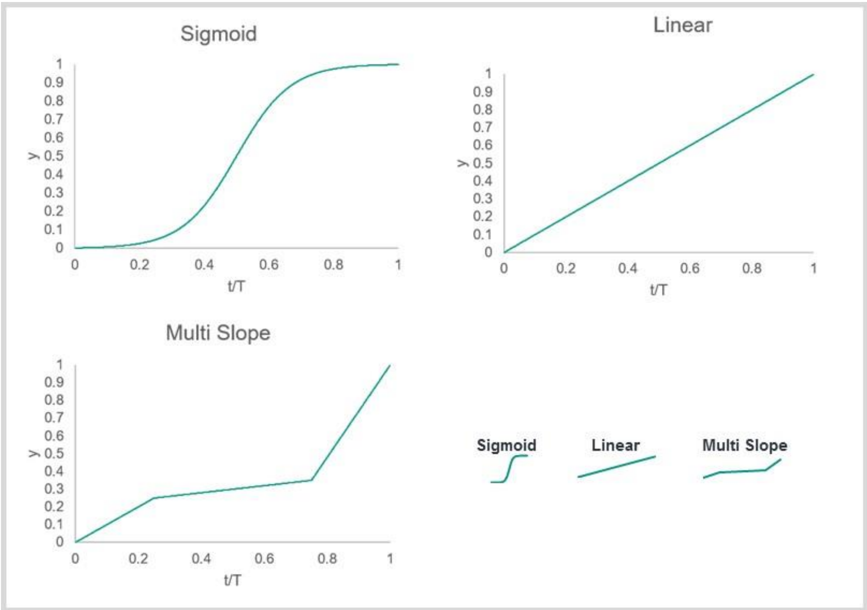


Figure 4-31: Visualization of three different formulas through graphs

Linking the interdependencies of technology

In Section 4.3, the relevant interdependencies among the technologies were defined. One technology can either be a prerequisite for another or supports another technology or have no interaction at all.

A prerequisite means that even if the dependent technology has already been implemented, it will not have any effect unless the prerequisite technology has also been implemented. If three technologies in a chain are dependent on each other as prerequisites, the last technology only has an effect if the first technology has also been implemented. In the case of support, however, the question of concatenation is not so clear-cut. Support means that a dependent technology becomes more effective by implementing another technology. If one technology supports another by 25%, the dependent technology has an effect of 1.25 once both are implemented. But how does the value change if there is another technology that supports the supporting technology by 10%? If series connection is not taken into account, this has no impact on the effect of the last technology in the chain. Otherwise, the support of the first technology carries over to the third. Since series connection in supporting interdependencies significantly increases the complexity of the model and requires very careful data collection, this has not been done. Otherwise, realistic behavior of the support factor cannot easily be ensured. Especially if circular chains are created, control would be significantly more difficult. It is also recommended to use an upper limit for the support factor. This should be technology specific and should be determined in consultation with the technology supplier and the technical expert.

In summary, in this work, chains are taken into account in the case of preconditions, but not in the case of support in order to simplify data collection.

Initial implementation level of technologies

The current level of the technologies could be modified by company input. The process of implementations consists of two elements: one flow and one stock. When the value of the stock reaches the number of days of the entire implementation, it will automatically switch to implement the next technology. Therefore, the key to the modification of the initial implementation level is to set the initial value of the stock. It can be imported from external Excel file, so that it is changed automatically in the model when the value has been changed in the Excel file by company. The simulation software Anylogic® is applied to interface with the properties of stock

As V&V technology for the System Dynamics (SD) model, monitoring is a good choice. The degree of implementation and the efficiency of each technology is displayed on a graph and the changes during the simulation run are checked with regard to the precondition and support. Thus, the logical consistency of the SD model and its interdependencies can be quickly ensured.

4.4.3 Modeling of Assembly Systems with Discrete Event Simulation

According to (Jondral 2013), Discrete Event Simulation (DES) models generally require more computing capacity and thus longer computing time. This is due to the operationally-oriented view of the system. Since the model is quite complex for the implementation strategy of smart automation technologies, the computing time of model needs to be taken into consideration. According to (Lütjen & Scholz-Reiter et al. 2014), the computing time required increases disproportionately with the level of detail of the model (x-axis) without, however, achieving significant increases in accuracy (see Figure 4-32). The optimal model complexity is given with a maximum discrepancy between computation time and accuracy. However, this point cannot be determined exactly either mathematically or experimentally. Therefore, it must be approximated. For this purpose, VDI standard 3633 proposes two different approaches: the *top-down* and the *bottom-up*.

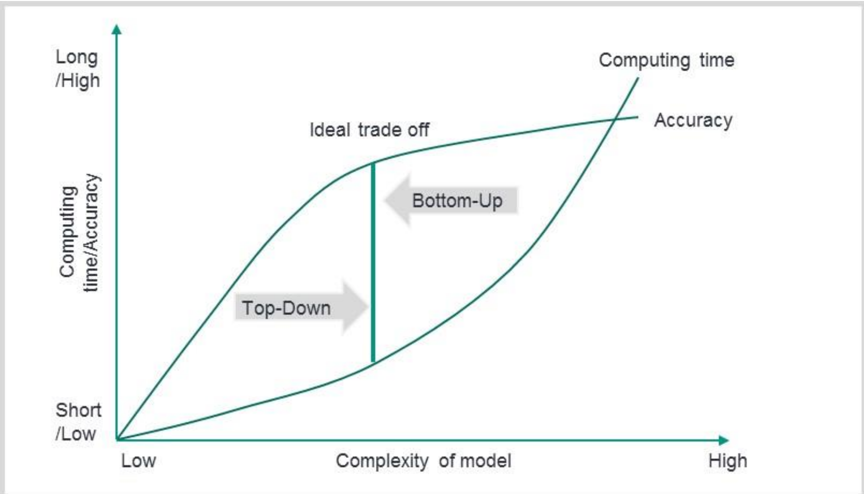


Figure 4-32: Dependence between the level of detail of the model and the expected result according to Lütjen and Herrmann (2014)

The top-down approach starts abstractly and gradually increases the complexity of the model. This requires a high level of abstraction on the part of the model creator and often leads to additional costs due to overly broad system boundaries. The bottom-up approach, on the other hand, synthesizes the whole thing step by step, starting with the details. This means that substructures are combined, thus reducing the complexity of the model. Since the starting point in this work is the value stream analysis (see Section 4.3.1), which breaks down the production system to the operative process level, the bottom-up approach is recommended. By measurements at the input and output of the respective subsystems, the process data and their probability distributions for the subsystem can be determined taking into account stochastic elements. Thus, the level of abstraction can be increased or the level of detail can be reduced. This facilitates the use of the bottom-up approach.

Modeling of workstation in Anylogic

By considering the context of assembly systems, there are three main elements of program to model the assembly process: Seize, Delay and Release. Seize represents the process of setting-up pallet for workpiece to the corresponding workstations. It can be connected to resource pool, which represents the process machines. Delay introduces the cycle time of the workstations. When the pallet is processed, Release represents the procedure of releasing the pallets from workstation. Restricted Area Start and Restricted Area End together with Queue are used to ensure only one piece of pallet could be processed by the workstation at one time. Subsequently, the select output simulates first pass yield procedure with the connection of two sinks, which stand for the waste and finished pallets (see Figure 4-33).

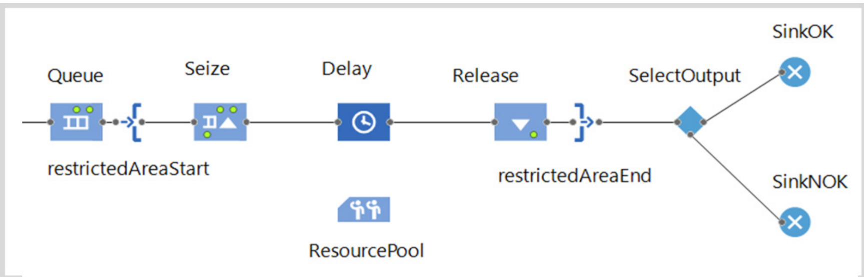


Figure 4-33: Modeling of workstation in Anylogic®

Metamodel based on Agent Based Simulation (ABS)

The ABS could be used to create the metamodel so that the developer can simply realize drag and work for further extension of the assembly system. As an example of the workstation, the agent *Workstation* could be created as the first layer model (see Section 2.6.3). This method of greatly improving work efficiency and shortening modeling time is therefore also called *modular modeling*.

For building a modular model in this part, it could be divided into following three parts (see Figure 4-34).

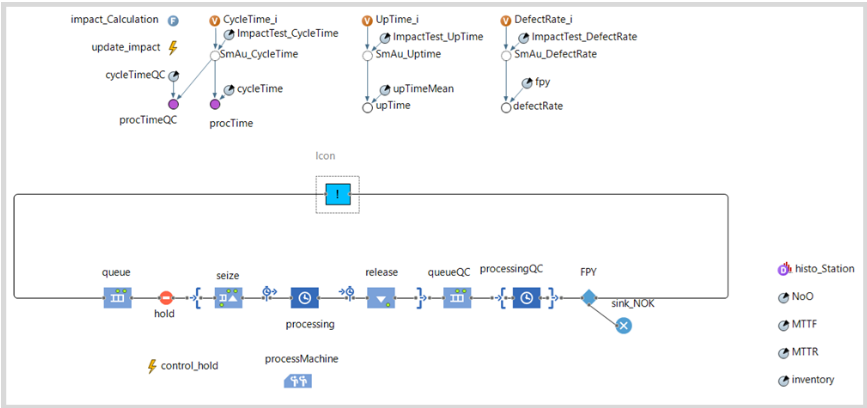


Figure 4-34: Metamodel of workstation in Anylogic®

In term of inside building of metamodel (part 1), all the model steps mentioned in above DES should be mapped inside the metamodel together. The icon of the metamodel is as a symbol to display the appearance of itself and could be considered as a normal DES element in the model level.

Regarding input data setup (part 2), the seven parameters (cycle time, uptime, first pass yield, inventory, MTTF, MTTR and number of operators) have been mapped at the metamodel layer. Under this precondition, these parameters could be modified individually in the properties of the metamodel agent. In addition, it could be controlled with the help of database as well. For outside connection to the metamodel (Part 3), there is invariably a source at the beginning and two sinks at the end of the Discrete Event Simulation (DES) model. Connected in the middle are the required workstations, of which quantity is not limited.

A verification and validation (V&V) technique for the DES and ABS model is monitoring and animation. In the latter case, the production sequence is graphically displayed in two dimensions using the simulation software and can be validated for accuracy together with the company's experts.

Modeling of KPIs

Once the assembly system has been modelled using DES, the selected and weighted KPIs in Section 4.3.2 can be integrated. The concrete calculation depends on the KPIs and the mapping in the company. A KPIs structure is generated in the previous and there are four aspects to be considered, which are explained below.

One of the difficulties in using KPIs is the choice of a suitable calculation period. Because several months or years are simulated for the implementation strategies, it is particularly important to choose the correct calculation period. If all values are included in the KPIs calculation from the start of the simulation, past values gain disproportionately in weight with longer simulation, which means that the key figure does not adequately reflect the current status. The effects of the introduction of new technologies are also less visible. If the period of time is too short, stochastic effects have a disproportionate influence on the key figure, which is expressed by a jumpy graph (Mauergauz 2016). Since the implementation of the technologies is measured in days and their effect is of primary importance for the study, it is recommended to consider only values of the last one or two weeks for the key figures.

Since key figures often have different characteristics, they cannot be offset against each other in a multi-criteria optimization, but must first be standardized on a comparable scale. The Formula 4.16 is used for the normalization of an individual key figure c_i. However, since c_i^{min} and c_i^{max} should not describe the theoretical, but the realistic minimum and maximum values of the key figure, these must be determined beforehand. According to (Weigert & Rose 2010), a rough estimate is sufficient. DES simulation can be used for this purpose by experimentally modifying the process data and thus building up an understanding of the key figure behavior. Together with the company's experts, c_i^{min} and c_i^{max} can then be roughly defined.

$$\gamma_i = \frac{c_i - c_i^{min}}{c_i^{max} - c_i^{min}} \qquad \text{Formula 4.16}$$

In addition, the Pareto sets should be displayed graphically (Weigert & Rose 2010). This can be done in two or three dimensions using Excel tables. If more than three key figures should be considered in the objective function, it is advisable to compare all possible subsets of key figures with each other in Pareto sets using several graphs. The objective of Pareto sets is a logical check of the weights. The weights should be adjusted so that the solution function is as close as possible to the center of all Pareto sets without changing the target value (see Figure 4-35).

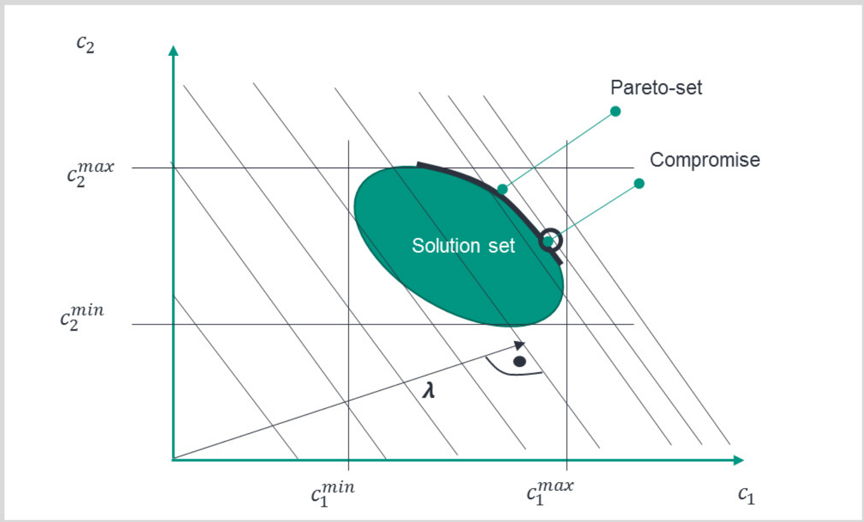


Figure 4-35: Optimal compromise with two target values c_1 and c_2 depending on the weighting vector λ (Weigert & Rose 2010)

The goal of the simulation study is to determine a strategy that will achieve the best possible improvement in production over the implementation period. In the long run it is not important which technology is introduced first. For the introduction period itself, this is again of great importance. Since this corresponds to several months to years, it is strategically important to choose an optimal implementation sequence, even if the result is the same at the end of the simulation. For this reason, the target value should be cumulated over the entire simulation period in order to take sufficient account of the change.

Finally, the implemented measures should be verified and validated. The key figures are graphically displayed in an overview over time and the curve is checked by the technical and simulation experts for its conclusiveness.

4.4.4 Hybrid Modeling with Process Data

The system analysis should enable the SD modeling of interdependencies and DES modeling of the assembly system. A value stream analysis is suitable for this purpose. According to its definition, a value stream comprises “”all activities (both value-adding and non-value-adding) that are necessary to move a product through the main flows that are critical to a product. The production flow from the raw material to the customer’s hands” (Rother & Shook 2018). The goal of value stream analysis is to identify and display the actual state of the production process with graphical support. The VSM provides not only the detailed process data, but also the system overview. A detailed description of the procedure for a value stream analysis is not included in this work. It should be noted that the complete value stream does not necessarily have to be modelled, but only the considered area and the respective previous and subsequent process step.

The process data (see Figure 4-25) can be as an interface to connect the SD model and the DES model. The DES model should map the process data as a parameter and read in the initial situation as well as its change through the effect of smart automation technologies (see Figure 4-36)

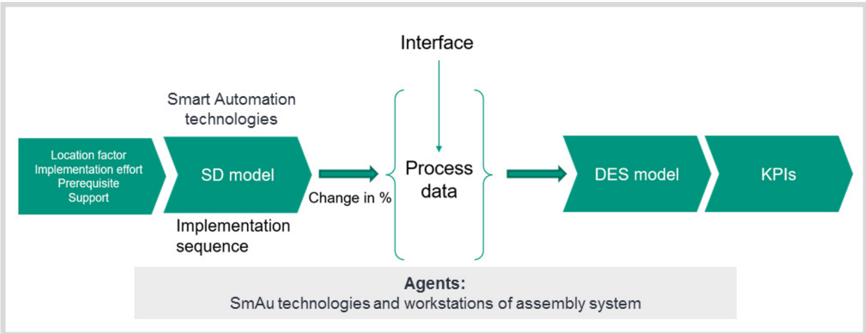


Figure 4-36: Process data as an interface in the hybrid model (A_Schrage 2019; A_Ding 2019)

Cycle time (t_{CT}), Uptime (v_{UT}) and first pass yield (v_{FPY}) are chosen as the interfaces. The defect rate has been applied to represent the first pass yield. Figure 4-37 shows the map of process data as interfaces. As an example, the dynamic variable smart automation_CycleTime is a variable with initial value of 1. Function impact_Calculation reads the input data of process impact from Excel table and calculate the current smart automation_CycleTime, which is decreased in the process of technology implementation yet always greater than 0. Then the Event update-impact make update the latest value and return it to smart automation_CycleTime.

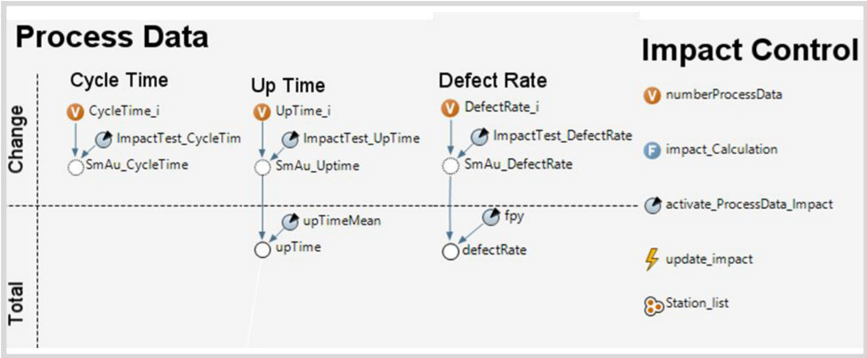


Figure 4-37: Process data as an interface in the hybrid model (A_Schrage 2019)

In addition, the runtime must be defined. This is the covered period by the simulation and consists of three modules. Usually, models are not initialized in more detail, so that they do not sufficiently represent reality at the start. As a result, buffer stores are often still empty and machines are not occupied. Accordingly, a certain amount of time should be allotted at the beginning, depending on the production system, which is necessary for the transient oscillation. Until the model is filled and represents a realistic state of the production system. During this time no technologies should be implemented in the model. In addition, the cumulative implementation time for the runtime must be taken into account. Taking into account the location criteria, how long does it take to implement all technologies regardless of their sequence? Finally, a phase-out duration must be considered in the runtime. If the simulation stops after the last technology has been implemented, the effects will not have time to unfold. It is recommended to equate the phase-out time with the longest smoothing period of a key figure (Drusinsky & Shing et al. 2005).

The sequence in which the technologies are introduced into the SD model is used as the control variable for the overall model. For later use as well as for verification and validation (V&V), an interface for simplified input of the manipulated variables should be created (Hechl 1995). Two methods are available as V&V techniques. One is monitoring by changing the sequence of introduction and logically tracing the influence on the key figures, and the other is a cause-and-effect analysis. In the latter, individual elements are changed and the consequences of the change are logically outlined step by step up to the key figures. Subsequently, it can be checked in the simulation whether the change affects the key figures as derived.

4.4.5 Experiment Design of Simulation

By considering of experiment design from Aull (2013), all simulations with the model created run according to the following procedure (see Figure 4-38). First, the freely selectable parameters (see Table 4-15) are entered into the input area. After starting a simulation run, the entered data are then transferred to the System Dynamics model. The start of each simulation is set to the current date, the simulation can be ended after 10 years or when the KPIs no long change, so that a sufficient period is simulated. Each simulation year is based on a twelve-month calendar with 30 days per month, and the time increment of the simulation is one day. Starting from the defined initial state, an approximate value for all variables in the simulation model is calculated for each simulation step size, which in turn represents the new initial state for the following simulation step. At the end of the simulation, the historical diagram of smart automation implementation and change of the KPIs are the final results displayed by the model.

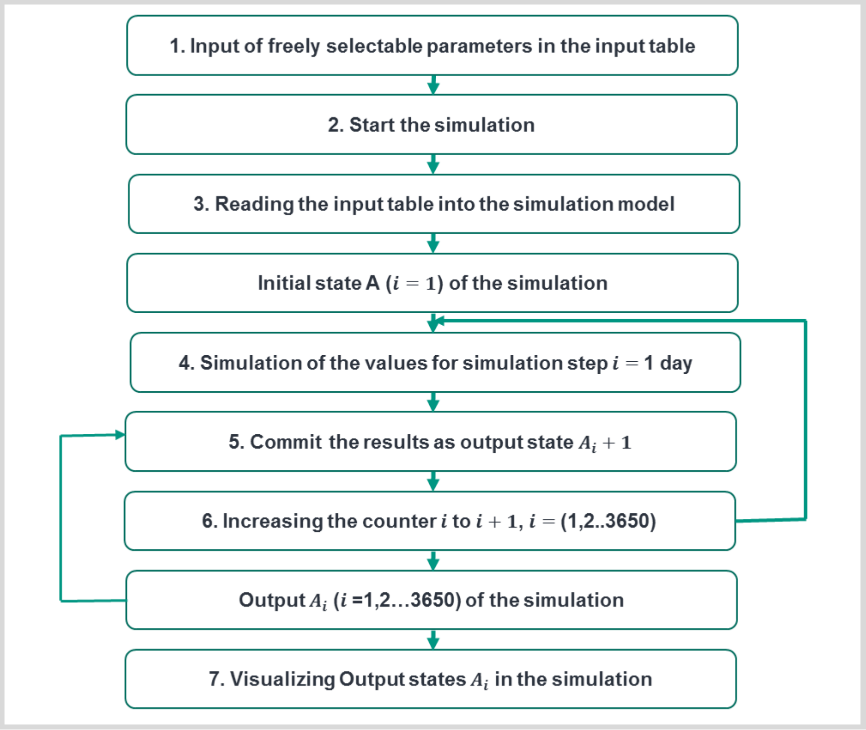


Figure 4-38: Flow chart of the experiment design of simulation (A_Zhang 2019)

Table 4-15: Setting of freely selectable parameter

No.	Parameter	Value	Remarks
1	Implementation Rank [#]	1-14	12 smart automation technologies and 2 wildcard for further potential technologies. Additionally, the maximum value can be increased by adding more wildcard. It depends on the number of technologies.
2	Initial level [%]	0-100	The initial value is between 0 (the smart automation technology is not used at all) and 100 (the technology is perfectly implemented).
3	Curve of implementation	Sigmoid, Linear, Multi slope	Gradient of implementation. Furthermore, the curves could be also selected during the implementation of

	the simulation. That means, developers can switch anyone of the three curves during the simulation, the implementation process will be automatically updated according to the current selection after the switch actions.

Summary

The creation of the hybrid model was introduced in this section, which happens in parallel and in close coordination with the data collection. The production system can be represented in a DES model. At the same time, the technologies, their interdependencies and their implementation can be mapped in an SD model. Finally, the two models can be connected via the initially determined process data to a hybrid model.

4.5 Derivation of Implementation Strategy

4.5.1 Description of Company Specific Assembly System in Simulation

To identify the specific assembly systems in simulation, the input data which make the assembly system distinctive need to be gathered. In this work, the input data are composed of five aspects: the specific location, status quo of assembly process, current situation of implemented technologies, important KPIs, and restrictions which need to be considered.

The specific location needs to be figured out. Afterwards, the location criteria can be adapted by combining the process factors which is defined by typical company in Section 4.3.1. Subsequently, the influence of location criteria on the smart automation technologies can be further analyzed. The specific adaption of interdependencies data based on Section 4.3.2 will be illustrated.

The data of assembly process needs to be reviewed as the basic input to create the assembly system in DES simulation. In this section, the data of value stream analysis are essential components.

The current status of implemented technologies must be analyzed, since some of the technologies have in many cases been partly implemented in the assembly system, such as RFID technologies. The initial implementation maturity degree will be considered by simulation, so that the simulated implementation strategy is more suitable to the specific assembly system.

Since the KPIs are a critical part for the assembly system, the specific KPIs need to be prioritized based on the company's concern. For example, a company may consider quality to be more important than cost or delivery time.

Regarding the constraints, the important factors will be specifically identified, such as the investment time limitation, and cost, which will be used to choose appropriate solvers.

After collecting the necessary data of a specific assembly system, the simulation can be adapted accordingly and provide the specific implementation strategy.

4.5.2 Optimization of Implementation Strategy of Smart Automation

After the input data were collected and outlined in Section 4.5.1, the object of this section is to derive an appropriate implementation strategy for the companies.

In order to make the decisions support, a deterministic model of binary linear programming is established. In this model, some basic assumptions have been made. First of all, all information that an enterprise can learn is accurate and remained. Specifically, the amount of capital, requiring time, the costs and benefits of technology can be seen as given values when a company makes decisions. These values will not change with time and conditions. This assumption is also consistent with the actual situation that companies take into account when working out plans. When making plans, companies usually make predictions on various indicators and ignore the changes of these indicators. In addition, it is assumed that there is no parallel implementation of technology development, which is required for the stability of the company's production process.

The decision binary variables can be defined as follow: $Tech_i$ means technology i.

$$Tech_i = \begin{cases} 1, & \text{if technology } i \text{ is selected,} \\ 0, & \text{otherwise} \end{cases} \qquad \text{Formula 4.17}$$

Considering company objectives, the KPI has been taken into consideration when it comes to the objective function. The investment on enabling technology can certainly bring advantages of KPI for companies, but it will accordingly have certain costs. Therefore, companies should consider the relationship between them comprehensively when making decisions. Specifically, in terms of KPIs, Quality (QUA), Cost (Cost), Delivery (DEL) and Availability (AVA) have been selected. According to the KPI structure, the following form of objective function can be obtained:

$$\text{Max}\, KPI = QUA \times \omega_1 + \text{Cost} \times \omega_2 + DEL \times \omega_3 + AVA \times \omega_4 \qquad \text{Formula 4.18}$$

where,

$$QUA = \sum_{n=1}^{k} v_{FPY_n} \times (1 + cof_n^{n-1}) \times Tech_n \qquad \text{Formula 4.19}$$

$$Cost = \sum_{n=1}^{k} v_{CT_n} \times (1 + Cof_n^{n-1}) \times Tech_n \qquad \text{Formula 4.20}$$

$$DEL = \sum_{n=1}^{k} n_{WIP_n} \times (1 + cof_n^{n-1}) \times Tech_n \qquad \text{Formula 4.21}$$

$$AVA = \sum_{n=1}^{k} v_{UT_n} \times (1 + Cof_n^{n-1}) \times Tech_n \qquad \text{Formula 4.22}$$

k is the total amount of technology available and Cof_n^{n-1} represents the mutual incentive coefficients between $Tech_n$ and $Tech_{n-1}$. ω_i is corresponding weight for KPIs. There are interdependencies between technologies, which is also mentioned by (Aull 2013). One of the interdependencies can be incentive, which means that the effectiveness or efficiency of the supported technology is improved by the implementation of the other. Therefore, the influence of different technologies on KPI indicators is not simply superimposed, but mutually reinforcing. This coefficient is determined by the characteristics of technology itself.

Next, the constraints are considered. The constraints faced by companies are more complex, but in general, most companies face the following constraints, as can be deduced based on the input of Section 4.5.1.

1) The total investment does not exceed a predetermined value.

2) The implementation days do not exceed a predetermined value.

These constraints are easy to understand. The capital a company can use is limited, so the total number of technologies it chooses, and the total investment have an upper bound. Meanwhile, when making a plan, time is the first thing that a company will take into consideration, so the implementation days must be predetermined.

The above constraints can be written as a linear function of decision variables. The formulas are as followed:

$$Invest_T = \sum_{n}^{k} Tech_n \times invest_n \leq Const_{invest} \qquad \text{Formula 4.23}$$

$$Days_T = \sum_{\mathrm{n=1}}^{\mathrm{k}} Tech_n \times D_n \leq Const_{days} \qquad \text{Formula 4.24}$$

where $Const_{invest}$ and $Const_{days}$ are all constant values that represent the maximal amount of investment and the requiring implement days respectively. D_n describes implementation days and $invest_n$ represents investment cost of individual technology. These could be identified by specific company.

4.5.3 Evaluation of Implementation Strategy

A large part of the interactions was quantified in Section 4.3 using expert interviews. Accordingly, it is necessary to ensure that the previously selected sequence of implementation remains stable in the event of deviations in the data. A suitable tool to perform a sensitivity analysis for such cases is the Monte Carlo simulation.

Monte Carlo simulations can be used for various purposes in which individual quantities are to be varied with a probability distribution. Accordingly, it can also be used for the sensitivity analysis of the selected sequence. *Sensitivity* means how much the output changes when there are deviations in the input. Robustness, on the other hand, would mean that similar results can be obtained with little adjustment of the model, should deviations occur. Therefore, the lowest possible sensitivity is desired (Zio 2013).

First of all, it is necessary to determine which parameters have to be varied. Theoretically, all values occurring in the model could be changed with Monte Carlo simulation. However, this would lead to a fuzziness of the results, since it is not obvious what caused the deviation of the output. Furthermore, there is a large amount of data empirically collected in the production system for which a deviation outside their already defined probability distributions is unlikely. Accordingly, the three data sets are focused since they were quantified by expert interviews and therefore have the highest degree of uncertainty. They include: the influence of location factors on technology implementation, the mutual support of technologies and the influence of technologies on process data. Based on (Kaiser 2014), it is assumed that expert estimates may well contain quantitative inaccuracies, but are qualitatively very precise. Consequently, only those values in the three data sets are varied for which there are correlations according to the experts. This means that values that are one or zero have no correlation or support and are therefore not changed in the Monte Carlo simulation. For this reason, no prerequisites are varied, since these are qualitative in nature.

After the parameters to be varied have been determined, the variation range must be defined. Since only limited information is available about the realistic distribution of the parameters, a symmetrical triangular distribution is recommended. The previously used value represents the mean value of the distribution and the deviation of the expert estimation is a maximum of 10% in both directions. In addition, it is necessary to determine how many simulation runs with differently varied parameters should take place. As a rule of thumb, the number of runs should at least correspond to the number of varying parameters (Rubinstein & Kroese 2016). It is also important that the seed is not fixed, otherwise the sensitivity analysis will only be performed on a single probability instance of the production system.

The result is a distribution of the target value. For detailed analyses, it is advisable to vary the three data sets both together and separately in a Monte Carlo simulation. The latter allows the identification of critical data with a large influence on the output values. The analysis can be done with simple statistical means. Doubilet & Begg et al. (1985) recommend the use of the mean value and the standard deviation. The mean value should correspond as closely as possible to the value previously determined in Section 4.3.2 and the standard deviation should be as small as possible. In order to evaluate the latter, the probability that the current order is better than the second-best order determined in Section 4.5.2, despite deviations, can be determined using the probability distribution determined.

5 Validation

In this section, the practical application of the approach defined in the previous section takes place. As already mentioned, the simulation model under investigation serves the evaluation and development of regionalized smart automation implementation strategies.

The practical applicability of the method must be proven and enabled in the validation. Therefore, the validation is carried out in cooperation and coordination with an industrial company.

5.1 Validation Setup and Procedure

This section is dedicated to the setup of the validation of the approach for regionalized smart automation implementation strategies. The aim is to describe a successive procedure for comprehensive verification of correctness and suitability as well as for simultaneous further development and improvement of the approach. The focus is primarily on the inclusion of expert opinions and the use of real data from a manufacturing company. Furthermore, the adaption of the simulation model's functionality according to the requirements of industrial companies to ensure its suitability for practical use plays also an important role within the developed approach.

Hence, besides on-site visiting to collect necessary basic data such as data of value stream mapping in terms of assembly systems, the validation consists of three major phases. First, the regionalized catalog is reviewed and subsequently, the interdependencies between the location factors, smart automation technologies and process data are discussed with experts from the company in the second phase. The third phase revolves around updating the model’s functionality according to their specific needs and characteristics. Last, in the fourth phase, the model is conducted based on the company’s input a suitable smart automation implementation strategy is formulated. The results are discussed with the company’s management. Figure 5-1 illustrates the validation procedure.

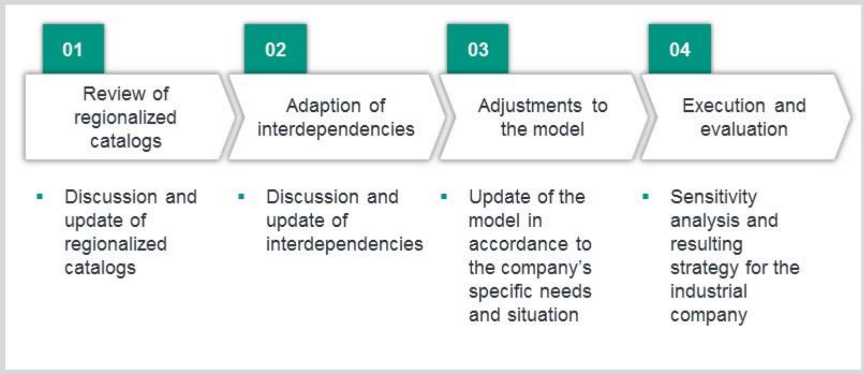


Figure 5-1: Procedure of the Validation (A_Thiele 2020)

5.2 Pilot Application with an International Manufacturing Business in China

The Beijing plant manufactures hydraulic pumps, motors and transmissions. The site in Beijing has about 1300 employees and produces in shifts. Part of the strategy of the Beijing plant is to become a leading user of Industry 4.0 applications and solutions. To achieve this goal, several solutions have already been implemented and documented (see Figure 5-2). One example is the use of RFID for replenishment in the production of pumps and motors, which has reduced the time needed to replenish the pumps from six to four hours.

As a result, the choice of this location as a support and information source offers an excellent opportunity to incorporate the experiences of the implementation process into the investigation. At the same time, the Beijing plant can also be seen as a potential user to develop the implementation strategy of smart automation technologies as part of an intelligent production strategy. Accordingly, the application of the proposed method is being carried out in close cooperation with the company and reflects the wishes and requirements of the company.

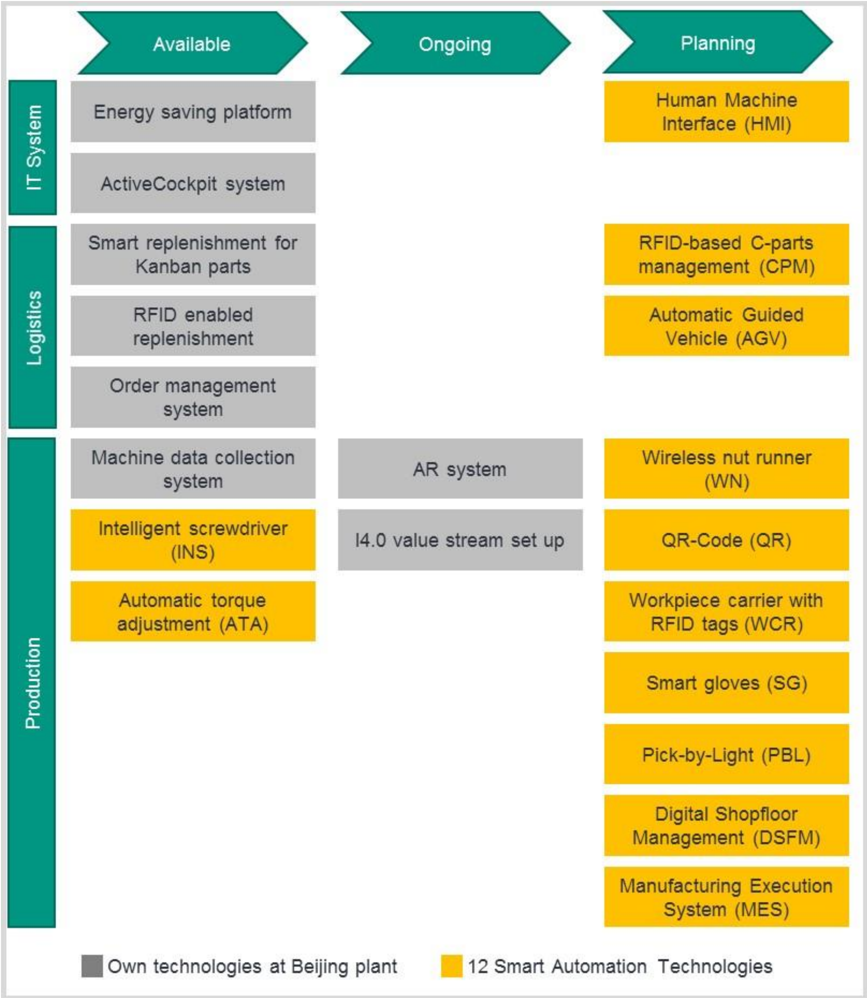


Figure 5-2: Overview of I4.0 Project Navigation at Beijing Plant

Object of validation

The assembly system of a control block is taken as the pilot in the validation. The reason is that the control block (see Figure 5-3) and the pump form the powerful heart of the excavator and t is also the point where further development of the flow sharing system starts. Therefore, the control block plays an important role in the product cluster. The research of its assembly system has a significant impact on the plant. Additionally, this kind of control block has also been demonstrated in GAMI test bed, where the experiments of the initial data collection were conducted.

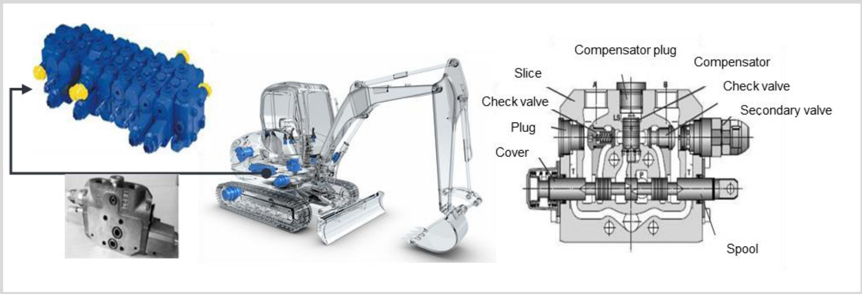


Figure 5-3: Control block for compact excavators

In terms of control block, the production process starts with the delivery of the raw materials and the production of the individual valve slice. During this process the blocks are milled and washed, and holes are drilled. Before the slices are sent to the assembly line, an optical quality inspection is carried out using an endoscope. In the assembly line, the assembly process of the individual slice to form a valve block is divided into the sections of slice assembly, block assembly and water bath leakage testing. After a functional test, the blocks are painted and finally packed and shipped. Since only the assembly process of the individual slice is of importance for this research, the processes are focused accordingly from the assembly of the slice and the composition to a block (see Figure 5-4).

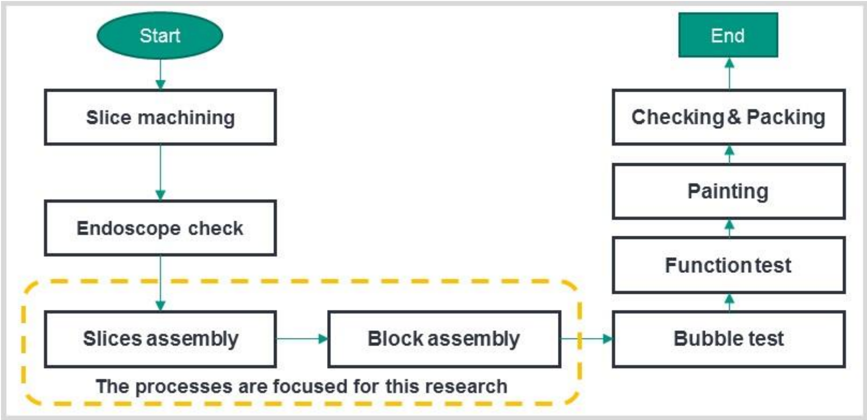


Figure 5-4: The overview of production process of control block

Problem definition

As Figure 5-2 showed, the I4.0 project navigation has already been developed in this plant. The technologies have been listed in the matrix compose with different perspective IT systems, logistics, and production on the one hand, available, ongoing and planning on the other hand. The advantage of I4.0 project navigation is to bring the overview of current and future advanced technologies. Nevertheless, it cannot provide a clear implementation strategy regarding the implementation sequence of technologies for the plant, especially for the assembly system of the control block, which is currently challenging the decision-makers. In terms of smart automation, the underlying problem is the difficulty of formulating a suitable implementation strategy for twelve selected smart automation technologies by considering the location factor influence of Beijing. For example, according to the plant manager, the introduction of an AGV is only worthwhile if the wage level in the region under consideration is above average and thus hiring workers is more expensive than an AGV. Furthermore, the impact of individual technologies and isolated solutions on specific applications can be assessed well. The integration of a whole range of technologies and their effects on the overall performance of the assembly system are more difficult to predict, especially because of the interdependences of technologies already mentioned.

5.2.1 Review of the Regionalized Catalogs

According to the output of Section 4.2, the identified catalogs were discussed with five experts from different departments of the Beijing plant. The experts agreed that taxes and energy costs do not play an important role for their plant since the ration between revenue and taxes is stable for the foreseeable future. The energy cost itself is not critical, but energy consumption by considering environment and sustainability is. In Beijing, there is strict regulation on the reduction of CO2 emissions to protect the environment. For this purpose, an energy efficiency team has been organized in the plant with aim to reduce CO2 emissions year after year. In term of the KPI catalog, the experts have agreed that the quality, cost and delivery as well as availability should be taken into account.

As the result, the identified catalog is agreed by experts. The reviewed catalog is introduced as followed (see Figure 5-5).

LoFa	SmAu technologies	KPIs
Labor costs	Pick-by-Light (PBL)	Quality
Cost of capital	Human Machine Interface (HMI)	Cost
Availability of skilled workers	QR-Code (QR)	Delivery
Staff turnover	Intelligent screwdriver (INS)	Availability
Taxes ■	Wireless nut runner (WN)	
Transport costs	Automatic Guided Vehicle (AGV)	
Energy costs ■	Automatic torque adjustment (ATA)	
Material costs	RFID-based C-parts management (CPM)	
Labor productivity	Workpiece carrier with RFID tags (WCR)	
	Digital Shopfloor Management (DSFM)	
	Manufacturing Execution System (MES)	
■ Notfocus	Smart gloves (SG)	

Figure 5-5: Revision of regionalized catalogs

5.2.2 Adaption of Interdependencies

As illustrated in Section 4.3.1, the company profile needs to be defined before the researcher can identify interdependencies between location factors and smart automation technologies. The Beijing plant is identified as Type 3, which is the focus type of this work.

Regarding the interdependency between location factors and smart automation technologies, further analysis of company profile is conducted for Beijing plant. The updating of the site profile using real data was done via interviews with experts and representatives of the site. With the help of employees from the controlling department, the location profile of Beijing plant is shown in Figure 5-6.

Location Factors		Indicator & unit	Level 1	Level 2	Level 3
1	Labor costs	Average annual wage [RMB]	< 60,000	60,000 – 100,000	> 100,000
2	Cost of capital	Weighted financing cost [%]	< 6 %	6% - 6.5%	> 6.5%
3	Availability of skilled workers		low	medium	High
4	Staff turnover	Staff turnover [%]	< 10 %	10% - 20%	> 20 %
5	Taxes	Total tax/ Turnover [%]	< 5 %	5% - 7%	> 7 %
6	Transport Costs	Transport cost/ Turnover [%]	< 3 %	3% - 10%	> 10 %
7	Energy costs	10kV electricity price [RMB/kWh]	< 0.50	0.50 – 0.65	> 0.65
8	Material Costs	Regional raw material cost [bn.RMB]	< 500	500 – 1,000	> 1,000
9	Labor productivitiy		low	medium	high

Not focused according to analysis of Figure 4.20

Beijing plant

Sample plant

Figure 5-6: Comparison between Beijing plant and sample company

Figure 5-7 demonstrates the difference between Beijing plant and the sample plant (benchmarking) in Section 4.3.2. The labor costs, the availability of skilled workers, staff turnover, transport costs, and material costs are lower, while the cost of capital is higher than benchmarking. For transferring to quantity value, benchmarking is taken as reference standard and given the threshold value 1.0. Based on the different level, the variable value could be 0.95 or 0.90 on the one hand, and 1.05 or 1.10 on the other hand.

Therefore, the qualitative comparison with the sample company is converted to the quantitative value (see Table 5-1), which will be calculated as the influence on smart automation technologies in the model. In the Table 5-1, the quantitative value of location profile for the Beijing plant are marked with green. The results indicate that except the cost of capital, the Beijing plant has lower cost than the sample plant in the fields of labor cost, transport cost, and material cost. Meanwhile, the Beijing plant has lower staff turnover and availability of skilled workers.

Table 5-1: Location profile with quantitative value of Beijing plant (A_Thiele 2020)

Location Factors	Indicator	Level 1	Value	Level 2	Value	Level 3	Value
Labor costs	Average annual wage [RMB]	<60,000	0.90	60,000-100,000	0.95	>100,000	1.0
Cost of capital	Weighted-financing cost [%]	<6%	1.05	6%-6.5%	1.0	>6.5%	0.95
Availability of skilled workers		Low	0.90	Medium	0.95	High	1.0
Staff turnover	[%]	<10%	0.90	10%-20%	0.95	>20%	1.0
Transport costs	Transport cost/Turn-over [%]	<3%	0.95	3%-10%	1.0	>10%	1.05
Material costs	Regional raw material cost [bn.RMB]	<5	0.90	5-10	0.95	>10	1.0
Labor productivity		Low	0.90	Medium	0.95	High	1.0

Based on the Table 5-1, the adaptive influence between location factors to smart automation technologies can be derived in Figure 5-7 based on the result of the sample plant in Section 4.3.2. For instance, the value of influence from Labor costs to QR-Code is 0.98, which equals to 1.03 (value of Sample company in section 4.3.2) multiplies 0.95 (value of Beijing plant by comparison with Sample company in Table 5-1).

The total influence can be determined by column multiplication. For example, the comprehensive influence of QR-Code technology is 0.91, which means the product of influence numbers in column T3 of Figure 5-7. This is done before the model is executed and the values are to be saved in an Excel spreadsheet. When the model is executed, for each technology that is modeled as an agent, the base effort is offset against the total influence of the location factors.

No.	Ab.	Vertical to Horizontal / Location Factors ↓	T1 PBL	T2 HMI	T3 QR	T4 INS	T5 WN	T6 AGV	T7 ATA	T8 CPM	T9 WCR	T10 DSFM	T11 MES	T12 SG
			B: Comparable Matrix - Enabling Technology ↓											
1	L1	Labor costs	1.00	1.00	0.98	1.00	1.00	1.02	1.00	1.00	0.98	1.02	1.02	1.00
2	L2	Cost of capital	0.90	0.90	1.00	0.86	0.86	0.92	0.86	0.90	1.00	1.00	0.86	0.90
3	L3	Availability of skilled workers	0.95	0.99	0.93	0.99	0.99	0.93	0.99	0.99	0.93	0.96	0.96	0.99
4	L4	Staff turnover	0.99	0.99	1.00	1.00	0.95	1.00	1.00	1.00	1.00	0.96	0.93	0.99
5	L5	Taxes	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
6	L6	Transport costs	1.00	1.00	1.02	1.00	1.00	1.00	1.00	1.05	0.98	1.05	0.98	1.00
7	L7	Energy costs	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
8	L8	Material costs	0.99	0.95	0.99	0.99	0.95	0.99	0.99	0.95	0.99	0.96	0.96	0.95
9	L9	Labor productivity	1.05	1.10	1.00	1.10	1.05	1.00	1.05	1.00	1.00	1.10	1.10	1.05
		Comprehensive Influence to Smart Automation Technology	0.88	0.92	0.91	0.92	0.79	0.86	0.88	0.88	0.88	1.04	0.80	0.88

Remarks of the matrix:

- 1.0=Neutral, ">1"=Positive correlation, "<1"=Negative correlation.
- The dark grey marked abbreviation of Location Factors means that the Location Factors has no significant impact on the Smart Automation technologies according to expert
- T1: Pick-by-Light (PBL), T2: Human Machine Interaction(HMI), T3: QR-Code (QR), T4: Intelligent screwdriver (INS), T5: Wireless nut runner (WN), T6: Automatic Guided Vehicle (AGV), T7: Automatic torque adjustment (ATA), T8: RFID-based C-parts management (CPM), T9: Workpiece carrier with RFID tags (WCR), T10: Digital Shopfloor Management (DSFM), T11: Manufacturing Execution System (MES), T12: Smart gloves (SG)
- Comprehensive influence means multiply the given influence number
- Each individual influence value of Beijing plant is calculated based on initial value of Sample company. e.g. The value of influence "Labor costs→QR" is 0.98, which equals to 1.03 (value of Sample company in Section 4.3.2) multiplies 0.95 (value of Beijing plant by comparison with Sample company in Table 5-1)

Figure 5-7: Adaption of interdependencies between location factors and smart automation technologies

In terms of interdependency among smart automation technologies, the experts of the Beijing plant illustrated the situation in their domain. It can be seen here that the individual technologies in particular support data-driven technologies such as Manufacturing Execution System (MES) or Digital Shopfloor Management (DSFM). Furthermore, the model is programmed in such a way that supporting and prerequisite dependencies are mutually exclusive. Considering that the experts are representative of different departments, it is not possible to give the specific weight for calculation of support ration among smart automation technologies. Thus, the average value according to the expert feedback is adopted. For instance, support ration from Pick by light (PBL) to Individual working instruction (HMI) is 10% based on one group of experts, while the other group of experts recommend the support ration could be 30%. Therefore, the value of support ration, which is used for further simulation, is decided as 20%. In addition, the maximum cumulative support is limited to 25 percent. The only exceptions here are the MES and

DSFM technologies, where the technology support can assume a maximum of 50 percent. Meanwhile, the experts shared the knowledge regarding technology prerequisite. For example, the QR Code (QR) is prerequisite for implementing individual working instruction (HMI) by the complex assembly systems. Similarly, Individual working instruction (HMI) is prerequisite for Intelligent screwdriver (INS). The adaption of interdependencies among technologies are introduced in Figure 5-8.

		Vertical to Horizontal	B: Comparable Matrix – Smart Automation Technologies ↓											
			T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
No.	Ab.	Smart Automation technologies ↓	PBL	HMI	QR	INS	WN	AGV	ATA	CPM	WCR	DSFM	MES	SG
1	T1	Pick-by-Light		20%	0%	10%	5%	0%	10%	0%	0%	20%	25%	10%
2	T2	Human Machine Interface	20%		0%	100%	15%	20%	25%	0%	10%	100%	100%	30%
3	T3	QR-Code	0%	100%		15%	20%	25%	15%	5%	5%	40%	30%	15%
4	T4	Intelligent screwdriver	20%	30%	0%		30%	0%	40%	0%	10%	100%	100%	15%
5	T5	Wireless nut runner	10%	20%	0%	20%		0%	20%	0%	10%	100%	100%	25%
6	T6	Automatic Guided Vehicle	0%	10%	5%	0%	0%		0%	20%	0%	40%	40%	0%
7	T7	Automatic torque adjustment	10%	10%	0%	100%	100%	0%		0%	10%	50%	25%	5%
8	T8	RFID-based C-Parts management	0%	0%	0%	0%	0%	20%	0%		0%	45%	45%	0%
9	T9	Workpiece carrier with RFID tags	20%	100%	5%	100%	30%	25%	100%	100%		100%	100%	10%
10	T10	Digital Shopfloor Management	5%	20%	15%	20%	20%	45%	0%	30%	5%		35%	0%
11	T11	Manufacturing Execution System	30%	45%	20%	35%	30%	45%	20%	25%	15%	100%		5%
12	T12	Smart gloves	5%	10%	0%	0%	0%	0%	0%	0%	5%	20%	10%	

The yellow marked cell means that it is the prerequisite technology (precondition)

Figure 5-8: Adaption of interdependencies among smart automation technologies

The basic expenditure of the technology implementation was also carried out within the framework of the validation in dialogue with experts from the company. The results of the interviews are shown in Table 5-2. The numbers marked in red indicate that the experts at the Beijing plant provided a different value in comparison with experts by technology providers in Section 4. More specifically, the lower values for INS and ATA are particularly striking. This is due to the fact that by considering specific industry domain, these technologies are supplied and implemented in advance and are part of the equipment of the assembly line.

The expert interviews and shop floor inspection also provide data on the initial implementation levels of smart automation technologies. The assembly line features the intelligent screwdriver (INS) in combination with the automatic torque adjustment (ATA) and is fully utilized. Therefore, an implementation level of 100 percent can be assigned to these technologies. The Workpiece carrier with RFID tags (WCR) and Human Machine Interface (HMI) have been installed from hardware perspective, nevertheless the integration of software is needed, and therefore the initial level is 50%. The QR-Code (QR) is just in the beginning phase, so the initial level is around 10%.

Table 5-2: Adaption of base effort for the implementation of the technologies without influence of location factors (A_Thiele 2020)

No.	Smart Automation	Efforts [days]	Initial implementation level [%]	No.	Smart Automation	Efforts [days]	Initial implementation level [%]
T1	PBL	60	0	T7	ATA	90	100
T2	HMI	180	50	T8	CPM	96	0
T3	QR	120	10	T9	WCR	78	50
T4	INS	90	100	T10	DSFM	365	0
T5	WN	84	0	T11	MES	288	0
T6	AGV	264	0	T12	SG	**180**	0

In order to obtain real data for the characterization of the assembly system, a value stream analysis was carried out with subsequent inspection and visit to the assembly line on the shop floor (see Figure 5-9).

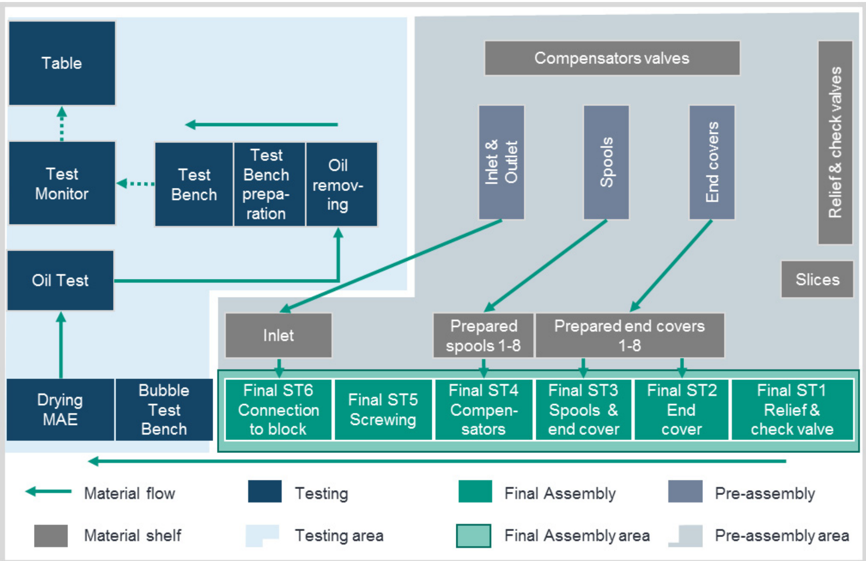


Figure 5-9: The layout of assembly system in Beijing plant

The assembly process takes place at six direct workstations in the line layout and can be provided with a different number of workers depending on the workload. The workpieces are transferred according to the FIFO principle and without intermediate storage.

The cycle time for the assembly of eight slices, which are then joined to form a block, is 14.8 minutes. Divided among the eight slices, this results in a cycle time of 111 seconds per slice. The cycle time for block assembly is 12 minutes and it results in a cycle time of 90 seconds per slide (see Figure 5-10).

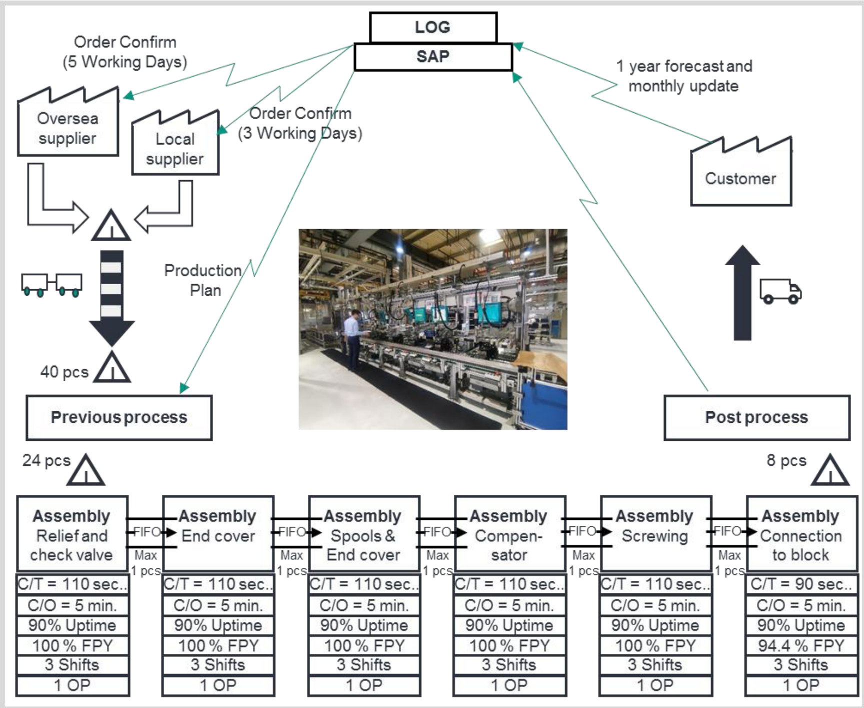


Figure 5-10: Value stream analysis of assembly system of Beijing plant

Based on further expert interviews with employees from the quality and maintenance areas, times for MTTF and MTTR can be determined. The uptime has been calculated and equals 90%. The value for the first pass yield (FPY) of the assembled blocks, i.e. the proportion of good parts to all parts, can be calculated using the rejection rate during quality inspection and is 94.4 percent. Table 5-3 summarizes all process data that resulted from the value stream analysis, shop floor inspection and the expert interviews. This also corresponds to the format in which the values are read into the simulation model and must also be subjected to a consistency check. For this reason, the units in which the data are available are also shown in Table 5-3.

Table 5-3: The process data based on Value Stream Mapping (VSM)

Station [No.]	**WIP** [Pcs]	**Cycle time** [Sec.]	**FPY** [Percent]	**Operator** [Quantity]	**MTTF** [Day]	**MTTR** [Day]	**Uptime** [Percent]
1	1[24]	110	100	1	6.42	0.07	90
2	1	110	100	1	6.42	0.07	90
3	1	110	100	1	6.42	0.07	90
4	1	110	100	1	6.42	0.07	90
5	1	110	100	1	6.42	0.07	90
6	1	90	94.44	1	6.42	0.07	90

The effects of the data on the performance of the assembly system are obtained by modeling the influence of the implemented technologies on the process data. These are of high relevance for the interface between the technology implementation and the assembly system. The collection of these data was carried out by means of experiments and was subsequently verified and validated by means of expert interviews with the Beijing plant (see Table 5-4). Finally, the cycle time, uptime and FPY are as key process data for further analysis.

Table 5-4: Influence of Smart Automation Technologies on Process Data

Influence of Smart Automation technologies on Process Data			
Smart Automation technologies	**Cycle Time**	**Uptime**	**FPY**
PBL	-0.02	0.03	0.33
HMI	-0.08	0.11	0.05
QR	-0.05	0.09	0.05
INS	0.00	0.00	0.33
WN	-0.07	0.03	0.33
AGV	0.00	0.10	0.05
ATA	-0.04	0.05	0.05
CPM	0.00	0.00	0.05
WCR	-0.06	0.08	0.00
DSFM	-0.05	0.05	0.10
MES	-0.04	0.06	0.00
SG	-0.05	0.00	0.10

According to the interdependencies between location factors and KPIs that were determined in Section 4.3.5, the experts of Beijing Plant emphasize Quality (on the other way is improvements in FPY), Cost (on the other way is savings in cycle time), Delivery (on the other way is reduction in WIP) and Availability (on the other way is improvements in uptime) are top four KPIs, which need to be focused on the validation. Since one fierce flow has been already implemented in the assembly of Beijing plant (see Figure 5-10), the WIP can actually be not changed. However, it is good to visualize the WIP in the simulation model by request. The connection between process data and these four KPIs plays an important role in analyzing the implementation strategy of smart automation.

Thus, the bilateral interdependencies are adapted based on the expert interviews at the Beijing plant, and these data are necessary input data for the modeling and simulation in the next step.

5.2.3 Adjustments to the Model

The basic structure and functionality of the simulation model has already been explained in detail in Section 4.4. A more detailed analysis, in which the technical implementation is discussed in particular, is provided in Section 5.2.3 (see Figure 5-11).

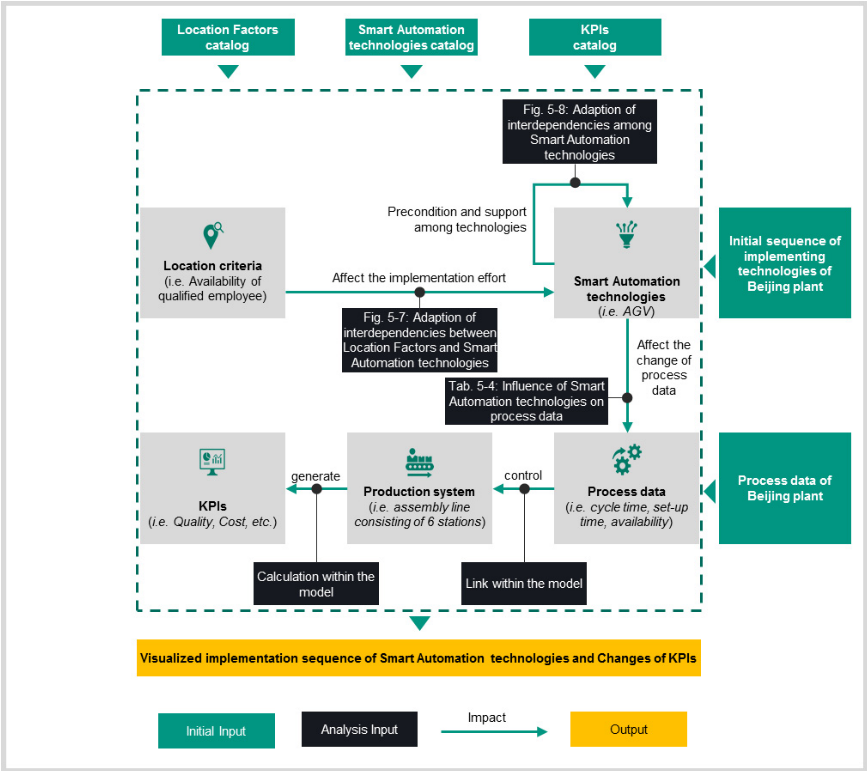


Figure 5-11: The framework of modeling and simulation for assembly system in Beijing (A_Thiele 2020)

Establishment of the simulation model

In this step the simulation model for the assembly system of the Beijing plant is described and modularized. The individual modules are examined in more detail. All data and functions used are listed within this Section.

For the Beijing plant, the simulation model is implemented in the AnyLogic© simulation environment. Its graphical user interface and the large selection of different libraries allow intuitive operation and adaptation of the model. When executing the model, the user is asked to define the ranking of the technologies and to determine the course of the implementation. The implementation process is implemented using system dynamic modeling. The technologies themselves are programmed as individual instances of an agent type. This enables the inclusion of the various interactions with other technologies and the location factors. The assembly system with its individual workstations is mapped using agent-based modeling. The processes and procedures within the individual workstations are represented by event-discrete sequence chains. System dynamic modeling is used to link the technology implementation and the assembly system. The performance of the assembly system is measured by means of various key figures, which are visualized in curve diagrams together with the implementation progress and the effect of the different technologies. Figure 5-12 gives an overview of the simulation model implemented in AnyLogic. A more detailed analysis of the individual components will follow later in this section.

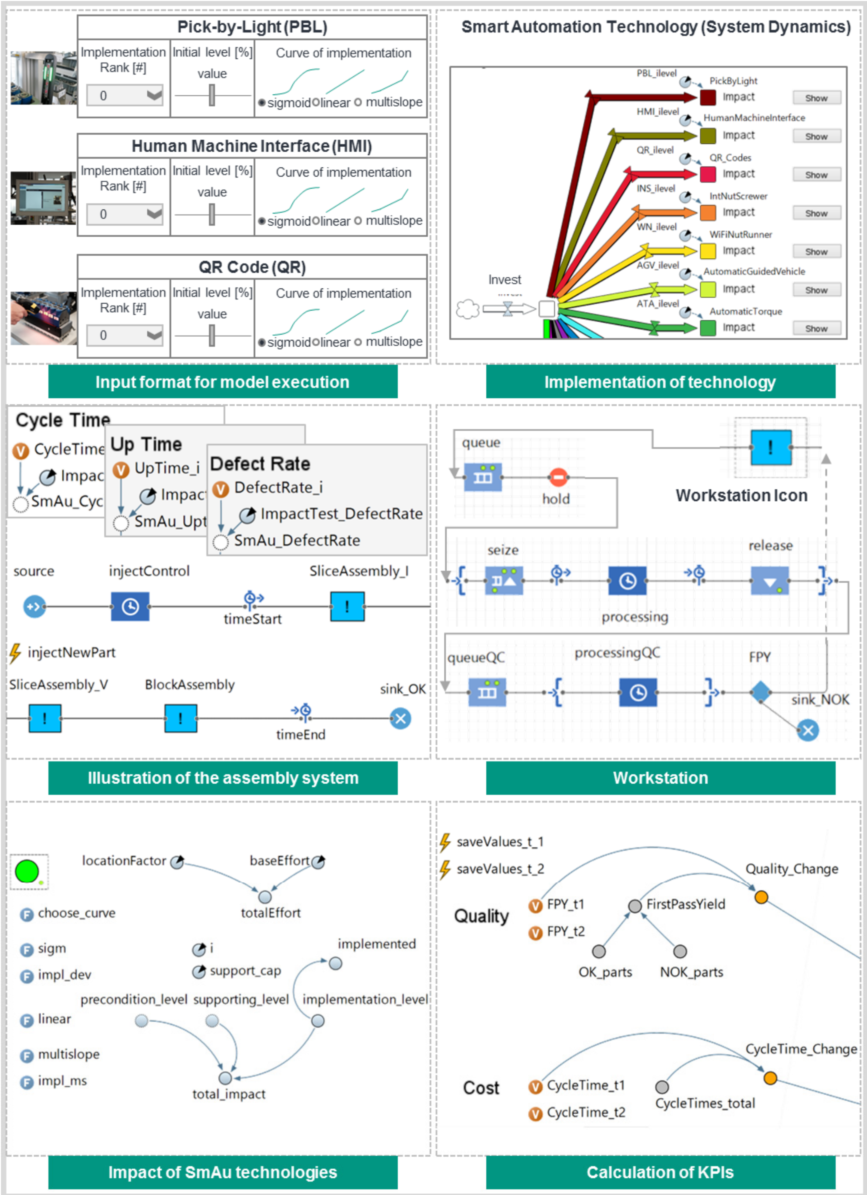


Figure 5-12: Overview of the simulation model

The input part includes the parameters of the selected technologies, which must be entered in the input mask during model execution, as well as the process data for the individual workstations of the assembly line and the characteristics of the various location factors. The data is linked to the model in various ways or implemented directly. All functions implemented in AnyLogic as well as the stored matrices for calculating the interactions between technologies, location factors and process data are part of the functionality. This section represents the largest part of the simulation model. The interface between the different agents and the system-dynamically or event-discretely simulated areas of the model is with particular importance. The calculation and the representation of the key figures, however, belong to the output part.

Analysis of the input part

The main components of the input part have already been identified. These include the catalogs of influence factors, the process data of the assembly system, the net of interdependencies of influence factors, the basic effort, the initial implementation levels and implementation curves of smart automation technologies, as well as the optimized sequence based on analysis of weighting of KPIs and constraints. Figure 5-13 provides an overview of the input part of the model and shows both the data sources and the links between the data and the simulation model.

First, the process data can be collected by means of a value stream analysis and expert interviews and should be saved in a Microsoft Excel™ spreadsheet so that it can be read in automatically by the simulation software. For each process step, the initial values for working in process (WIP), cycle time (CT), first pass yield (FPY), number of operators (#OP), mean time between failures (MTBF), mean time to repair (MTTR), and uptime should be recorded. Second, the net of interdependencies should also be saved in an Excel spreadsheet. Third, the data on the implementation status and effort of each technology must also be adjusted before the model is executed. The basic efforts for implementing the technologies are given in the number of days, while the initial implementation levels of the individual technologies in percent need to be recorded. In addition, the implementation curves can be determined according to the preference of plant. Finally, the initial sequence in which the technologies are to be implemented are randomly figured out at first.

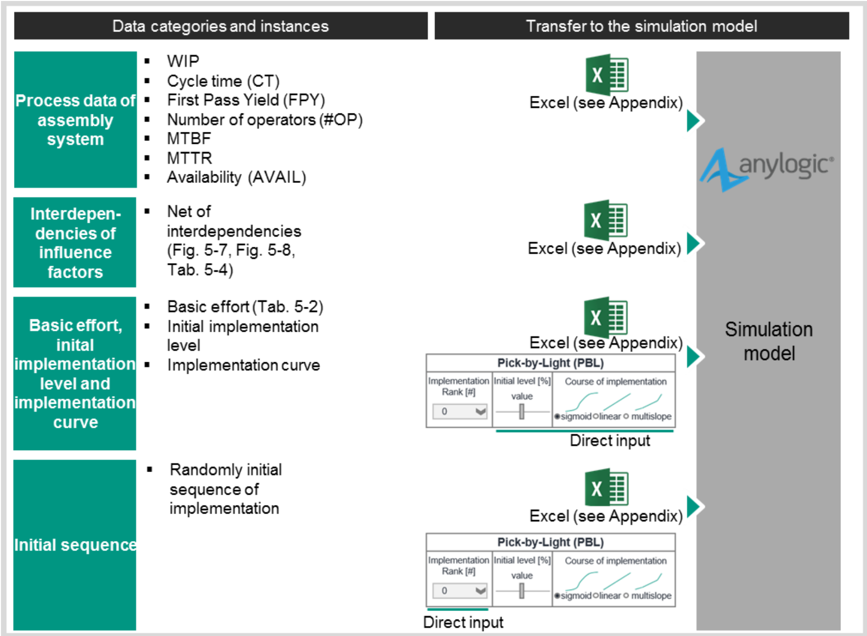


Figure 5-13: Input part of the model (A_Thiele 2020)

Analysis of the functioning

The investigation of the mode of operation essentially includes the presentation and implementation of the cause-effect relationships. This includes the three matrices, which contain the interactions between technologies, location factors and process data. Furthermore, the control and mapping of the assembly system and the systematics of key figure measurement form an elementary part of the mode of operation.

The first correlation within the functioning of the model is the impact of the location factors on the effect and implementation of smart automation technologies. The comprehensive influence can be determined by column multiplication (see Figure 5-7). This is done before the model is executed and the values are to be saved in an Excel spreadsheet, as already described in the input part. When the model is executed, for each technology that is modeled as an agent, the base effort from Table 5-2 is offset against the total influence of the location factors.

Another significant influence on the effect of the technologies is created by their combination. The model distinguishes two types of interdependence (see Figure 5-8). First, one technology can be regarded as a prerequisite for the effectiveness of another technology, whereby the dependent technology only develops its effect when the prerequisite technology is implemented. Secondly, the support means that a dependent technology becomes more effective by implementing another technology.

The effects of the data on the performance of the assembly system are obtained by modeling the influence of the implemented technologies on the process data (see Table 5-3). These are of high relevance for the interface between the technology implementation and the assembly system.

The mapping of all interdependencies between technologies, location factors and process data in the simulation model is done by means of hybrid modeling. The interdependencies between the technologies are implemented by agent-based modeling (ABS). Figure 5-14 shows the instance of such a technology agent. The number of days required for the complete implementation is calculated by the model based on the basic effort and the influence of the location factors. The parameter “precondition_level” expresses whether a prerequisite technology has already been implemented. Furthermore, the supporting effect of other technologies on the considered technology is included by the parameter “supporting_level”. Together with the parameter “implementation_level”, which represents the current progress of the implementation, the total influence of the technology is calculated.

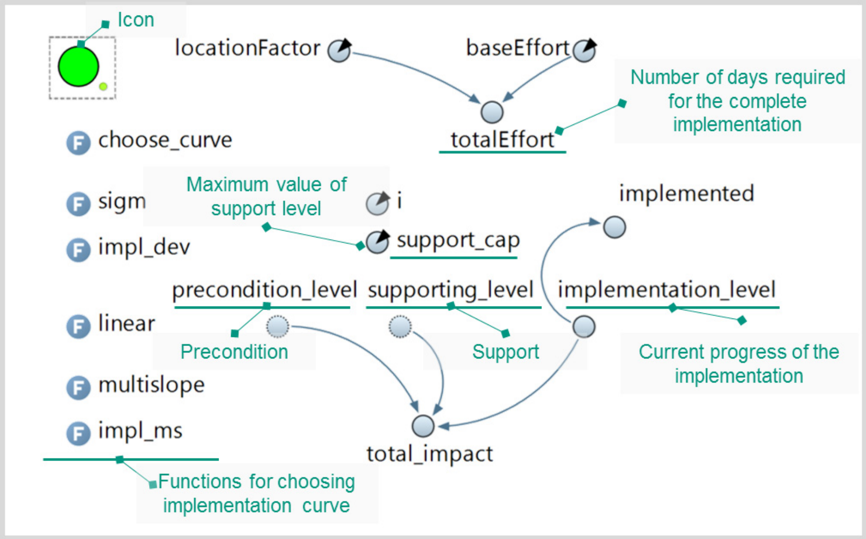


Figure 5-14: Modeling of smart automation technology based on agent-based modeling ABS

The assembly system in which the smart automation technologies are to be implemented is also modeled on an agent-based and discrete event basis (shown in Figure 5-15). Here, each processing station is an instance of the workstation agent as meta-model, within which an event-discrete process chain is defined, which is represented by different modules of a modeling library within the simulation software. At the beginning of this process chain, the workpieces are waiting to be machined. This is followed by the setting up of the machine, the actual work process and the release from the machine. The workpiece is delivered to the subsequent quality inspection and the result of the inspection determines the first pass yield (FPY). Faultless parts move on to the next station, whereas defective parts are sorted out from the simulation.

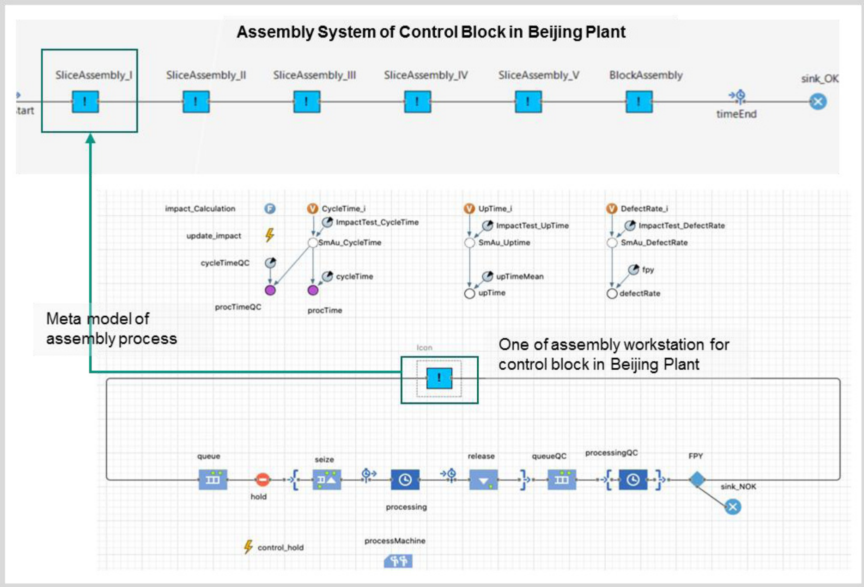


Figure 5-15: Modeling of assembly process based on ABS and DES

Also modeled within this agent, is the link between the technological influences and the process data and thus the effect on the performance of the assembly system. The function “impact_Calculation” calculates the new cycle time “SmAu_CycleTime” caused by the smart automation technologies, which then flows into the calculation of the new processing time for the workstation. The same logic is applied to both uptime and quality rate. The system dynamic relationships shown in the middle of Figure 5-15 are therefore used to control the performance of the assembly system. Here the lower dynamic variables “procTimeQC”(the time for visual check inside of assembly process), “procTime”(the time for pure assembly activities), “upTime” and “defectRate” are directly linked to the corresponding blocks of the event-discrete process chain within the modeled station, In this work the procTimeQC is negligible, since only a very short time for visual check are spent.

Control and progress of the implementation of the technologies are achieved by means of system dynamic modeling. Two stocks simulate the implementation effort of the technologies. The limit of the receiving stock corresponds to the number of days influenced by the location factors. Once a technology is fully implemented, the implementation of the next technology will start according to the initial sequence previously defined by the user. The parameters and events required to control the implementation are shown in Figure 5-16.

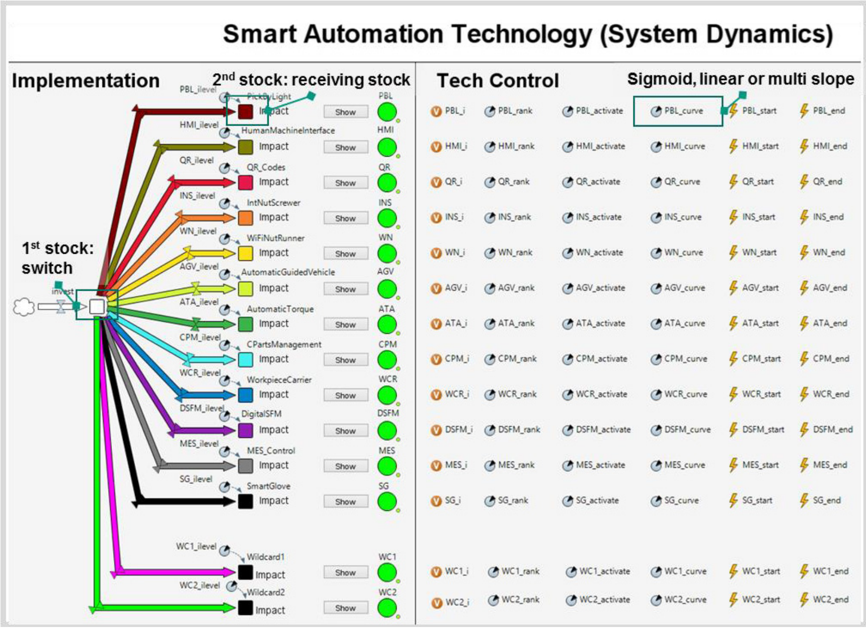


Figure 5-16: Modeling of Implementation of smart automation based on System Dynamics (SD) (A_Thiele 2020)

Analysis of the output part

The output part of the simulation model is made up of various key figures that reflect the performance and operational behavior of the assembly system. These key figures are calculated in the simulation model using dynamic variables that obtain their values from the modeled assembly line. The calculation logic of the key figures is shown in Figure 5-17. The key figure “Quality_Change” calculates the improvement in the quality rate over time, whereby the quality rate after the one-week settling phase is divided by the current quality rate during the technology implementation. The rest key figures follows the similar calculation logic as the key figures Quality.

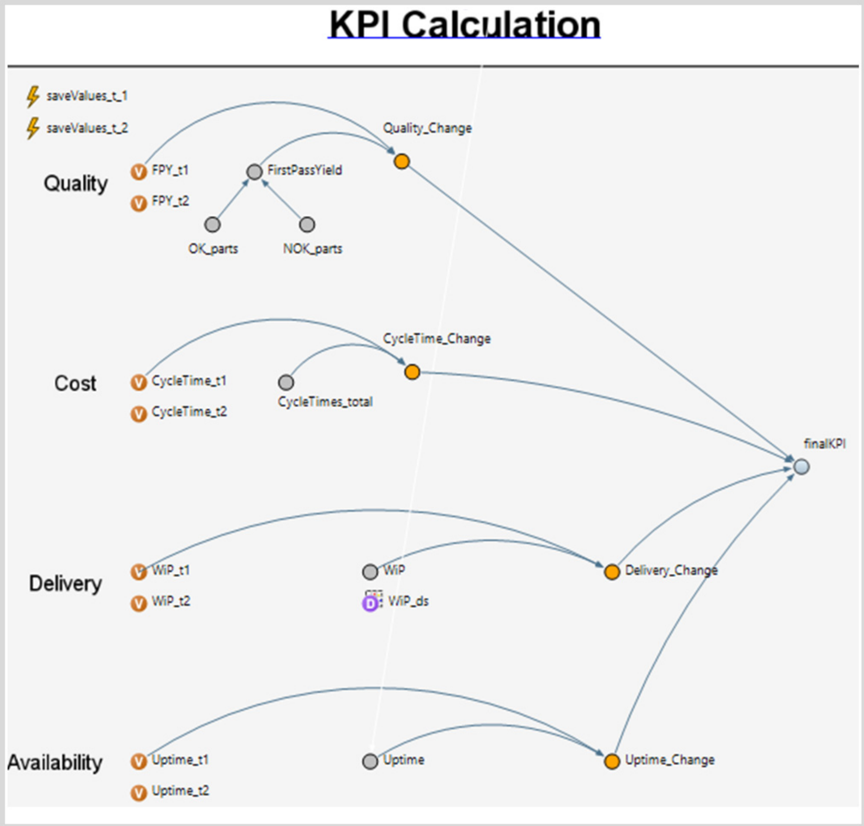


Figure 5-17: Modeling of KPIs calculation

Verification and validation of models

The verification and validation (V&V) of models composes of three major aspects, namely the input part, the functioning and the output part. Since the input part has been already mentioned in Section 5.2.2, the other two aspects are illustrated in the following.

In term of functioning, the methodology of dry run (testing) in combination with monitoring creates the possibility to recalculate the implementation of a technology on paper and then to verify the result with an isolated experiment in the simulation model. In this way, the correctness of the model can be specifically checked. Using the Wireless nut runner (WN) and Pick-by-Light (PBL) technologies as examples, the individual aspects of the functioning of the model can now be verified. From the location characteristics of the Beijing site, a value of 0.79 is obtained for the Wireless nut runner (WN) technology (see Figure 5-7). The basic effort is 84 days (see Table 5-2). Consequently, this results in an adjusted implementation time of 106.33 days. In the simulation model, the implementation period is 106.09 days. Without the conditional technology Automatic torque adjustment (ATA), the Wireless nut runner (WN) technology should not have any influence on the key figures or the implementation of another technology. This becomes clear if the Pick-by-Light (PBL) technology is implemented directly afterwards. The special feature of the Pick-by-Light (PBL) technology is that it has no conditional technologies, which means that its effects can be seen regardless of its ranking. Although Wireless nut runner (WN) should actually support the Pick-by-Light (PBL) technology by a factor of 0.1 (see Figure 5-8), the overall effect of Pick-by-Light (PBL) without the fulfilled precondition of Wireless nut runner (WN) remains at 1. This effect relationship is also represented in the model correctly.

The event validity test can be used to further refine the previous experiment. Since Workpiece carrier with RFID tags (WCR) represents the prerequisite technology for Automatic torque adjustment (ATA) and ATA in turn conditions Wireless nut runner (WN), the effect of Wireless nut runner (WN) would only have to unfold with the implementation of Workpiece carrier with RFID tags (WCR). An experiment with the sequence Automatic torque adjustment (ATA), Wireless nut runner (WN), Workpiece carrier with RFID tags (WCR) should prove this connection. Automatic torque adjustment (ATA) and Wireless nut runner (WN) can only develop their effect when the event of Workpiece carrier with RFID tags (WCR) implementation occurs. This should also occur linearly in the context of a linear implementation curves. Figure 5-18 contains the result of the event validity test. Here it is clearly evident that the effect of the technologies is only generated with the implementation of Workpiece carrier with RFID tags (WCR). The figure also shows that the verification and validation (V&V) measures are applied in combination. Thus, the animation and cause-effect graphs support the V&V process.

Figure 5-18: Event validity test of smart automation technologies (A_Thiele 2020)

Another meaningful V&V measure is the limit and error implementation test. The two limits of the implementation strategies to be tested by the simulation model are the implementation of no technology or all technologies at the same time. Consequently, it would be expected that in the first case, there would be no effect on the performance of the assembly system due to the technologies. In the second case, it is to be expected that all technologies will have their full effect approximately simultaneously and that the simulation model will be automatically terminated after a period of 60 days of settling of the simulation model, the longest implementation period and a subsequent 60-day stable phase. According to theoretical calculations, this should be the MES technology with an implementation period of 360 days (Basic effort days 288 in Table 5-2 is divided by comprehensive Influence of location factors 0.8 in Figure 5-7). Consequently, the simulation model would have to terminate automatically after 480 simulated days. Figure 5-19 shows the results of the two limit tests and confirms the assumptions made, thereby increasing confidence in the correctness of the model.

The measure of the targeted error implementation can be recognized by the calculation of the implementation efforts. For example, if a value of 0.5 is assumed for the site-specific support factor, the implementation time would have to be doubled. A simple isolated experiment on the WCR technology reflects this constructed fact. Instead of the basic implementation period of 78 days, it is now 156 days. This finding also helps to prove the correctness of the model.

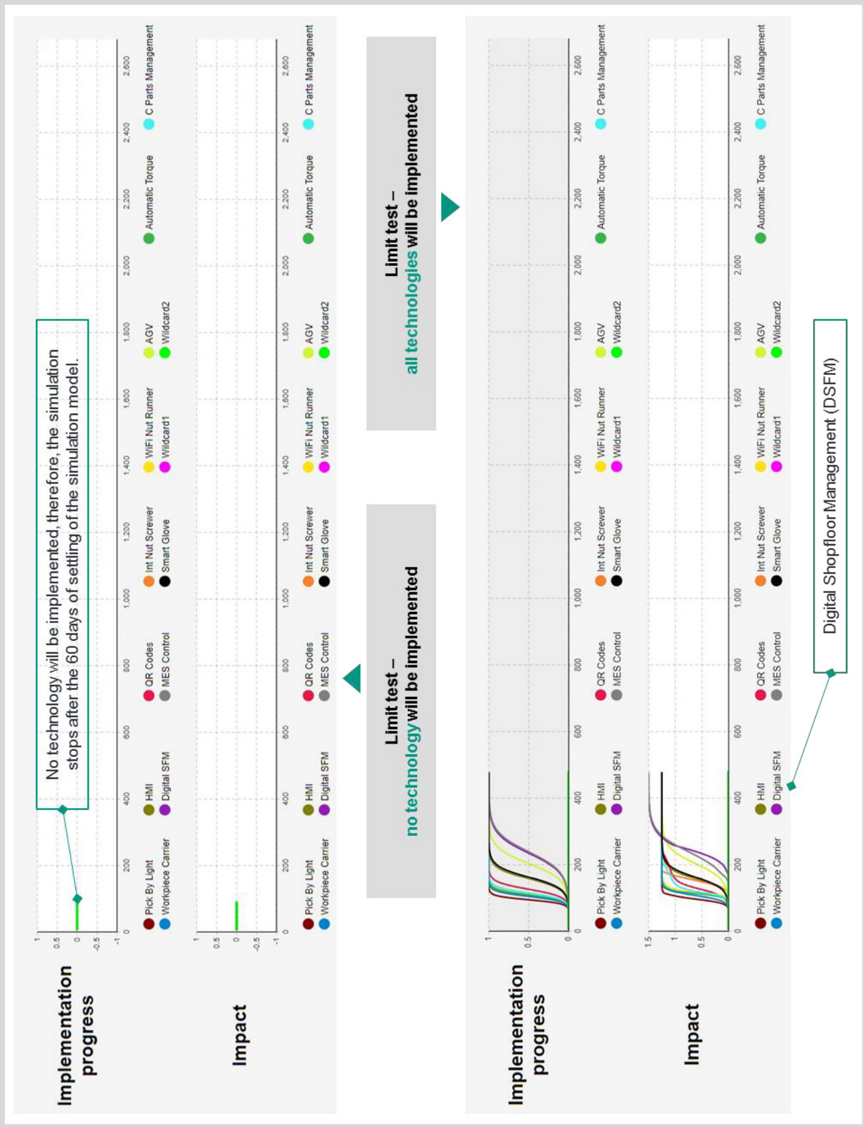


Figure 5-19: Limit test for implementation strategy

The V&V of the output part mainly comprises the verification of the KPIs generated by the model. Since the KPI structure is the basis for decisions on an implementation strategy by the management of the company, the correct calculation of the key figures and their suitability is of particular relevance (see Figure 5-20).

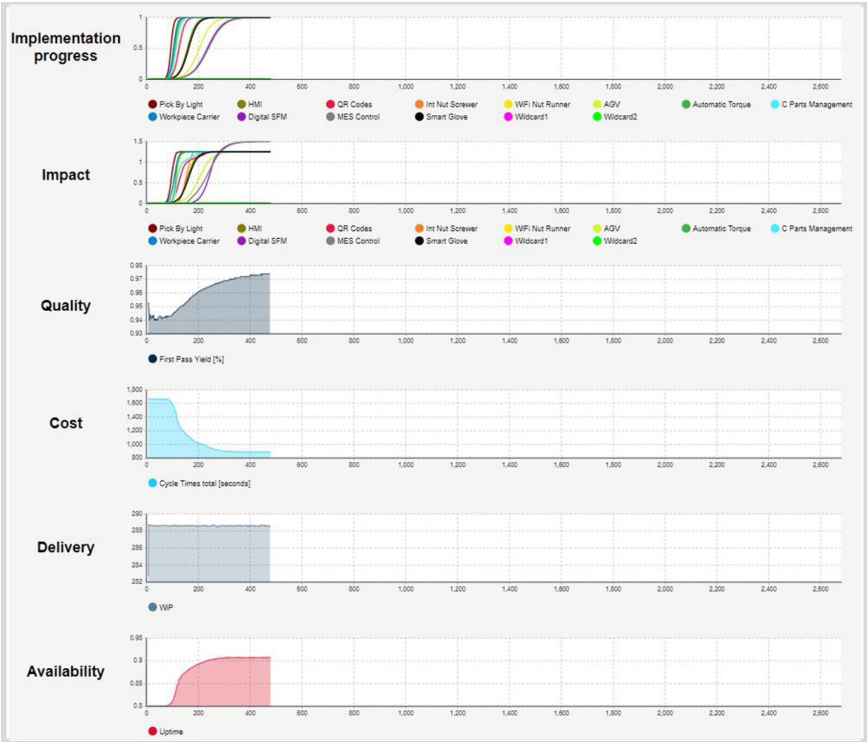


Figure 5-20: Limit test for KPIs

Experiment Design of Simulation

Based on the Section 4.4.5, the experiment design of simulation for the Beijing plant is illustrated as follows.

It is possible to consider more than the 12 technologies already identified. In principle, the simulation model is designed in such a way that the twelve technologies can be exchanged at will. However, this requires some renaming of variables and instructions in the code. The data used in the matrices must also be collected for the new technologies and entered in the corresponding Excel tables. In order to prevent the adjustments in the program code, but still be able to include new technologies in the model, two placeholder technologies are modeled. These are implemented in the program code as wildcard_1 and wildcard_2 and can be assigned any new smart automation technologies. The run indices and variable fields within the program code must be adapted accordingly. For the user of the model, only the data for the input part and the functionality of the model need to be entered into the Excel tables. Thus far, a total of 14 technologies can be considered within the model, but it can be easily extended by adding the new “wildcard_x”.

The KPIs are based on the Quality Cost Delivery Availability (QCDA) framework of the industrial company. Quality, Cost and Availability have been measured by quality rate, cycle time, and uptime, respectively. Delivery is represented by the amount of Work In Process (WIP), which can be automatically calculated in the simulation model. In addition, the model's settling phase has been increased to 60 simulated days. At the end of the 60 days, the current values of the key figures are stored. This happens at time t_1.

The quality is still recorded via the First Pass Yield (FPY) and is calculated from the proportion of parts found to be good in relation to all parts produced. The influence of smart automation technologies on machining times is measured and mapped by the sum of the shortened cycle times, which consist of cycle times for machining and quality control (visual inspection). For this purpose, the individual times from each station must be added together. A cost rate can be applied to the cycle time saved, which converts the time saved into savings in operating costs. The delivery improvement is represented by reduction of Work In Process (WIP). Additionally, the availability rate of the assembly system is represented by uptime. The increased availability is based on improvement of uptime.

All KPIs have in common that they are recorded after the settling phase and thus before the first implementation of the technologies, in order to reflect the status quo. In the further curve of the implementation of the technologies, the absolute change progressions of the four key indicators are shown in curve diagrams. A further curve diagram also shows the rate of change of the four key indicators in relation to the status quo. This enables the visualization of the influence of the technologies on the key figures in comparison to a scenario without implemented smart automation technologies. After all technologies are fully implemented, the current values of the KPIs are stored in static variables. This happens at time t_2. A direct comparison with the variables at time t_1 enables an exact calculation of the effects of the smart automation technologies on the KPIs. Figure 5-21 shows the key figure structure including the visualization using the example of a randomly selected implementation strategy.

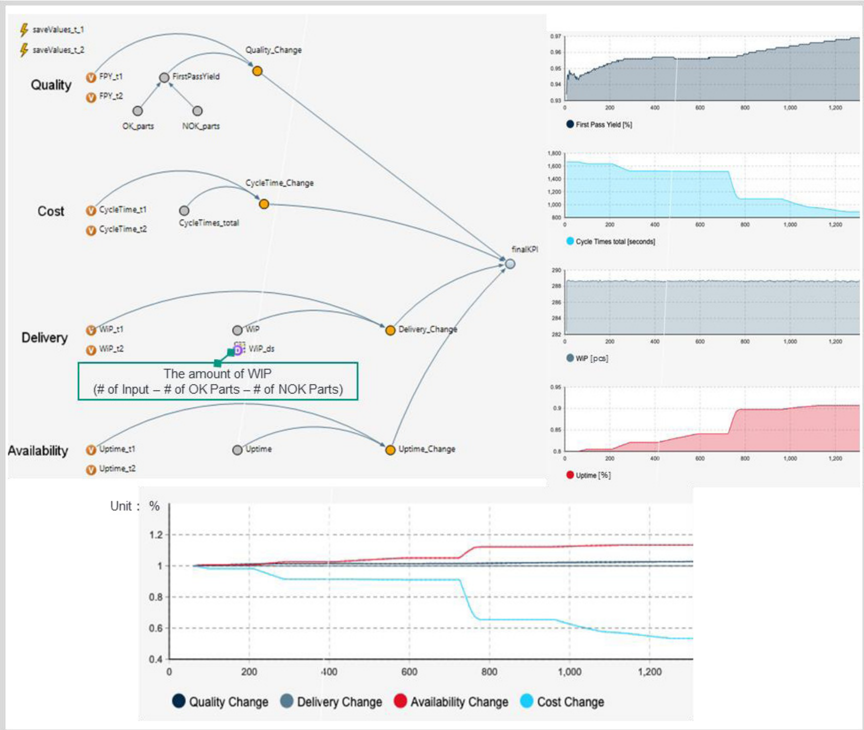


Figure 5-21: Structure and visualization of KPIs (A_Thiele 2020)

5.2.4 Derivation of Implementation Strategy for the Beijing Plant

Description of Specific Assembly System in Simulation

According to the procedure in Section 4.5.1, the input data for the specific assembly system for control block SX12 are gathered, which are composed of five aspects.

The specific location and location criteria have been achieved. The interdependencies, in particular, the impacts among location factors, smart automation technologies and KPIs were adapted.

The data of assembly process, which are used for simulation model, were obtained through on-site value stream mapping analysis.

The current status of implemented technologies were analyzed. The smart automation technologies, such as Intelligent screwdriver (INS) and Automatic torque adjustment (ATA), were well implemented. Thus, the initial level was 100%. The Workpiece carrier with RFID tags (WCR) and Human Machine Interface (HMI) were installed from the hardware perspective, nevertheless the software needs to be integrated, therefore, the initial level is 50%, the QR-Code (QR) is just in the beginning phase, so the initial level are around 10%. Additionally, the initial level of the remaining smart automation technologies that have not been started so far is zero.

According to the management board of the Beijing plant, the KPIs such as Quality, Cost, Lead Time and Availability are significant indicators with same priority. Therefore, the weight for these four indicators are equal.

The constraints have also been analyzed and listed. The total investment and the implementation days are two important constraints. The set-up cost of smart automation technologies as investment are carried out based on the input by technology providers (see Table 5-5). The implementation days are relevant to base efforts of smart automation technologies according to Figure 5-7 and Table 5-2.

Table 5-5: Set-up costs of smart automation technologies

Smart Automation technologies ↓	Unit (technology solution)	Set-up Cost (RMB)
Pick-by-Light (PBL)	1	2400
Human Machine Interface (HMI)	1	25,000
QR-Code (QR)	1	11,000
Intelligent screwdriver (INS)	1	100,000
Wireless nut runner (WN)	1	120,000
Automatic Guided Vehicle (AGV)	1	200,000
Automatic torque adjustment (ATA)	1	35,000
RFID-based C-parts management (CPM)	1	100,000
Workpiece carrier with RFID tags (WCR)	1	57,500
Digital Shopfloor Management (DSFM)	1	700,000
Manufacturing Execution System (MES)	1	400,000
Smart gloves (SG)	1	80,000

Optimization of implementation strategy of smart automation technologies

Following a step by step process for turning a problem statement into a mathematical statement, the optimization model will be adapted specifically to the assembly system of the Beijing plant.

According to Section 4.5.2, the problem is that Beijing plant could not derive the proper implementation sequence for smart automation technologies so as to efficiently maximize the improvement of KPIs. The challenges lie in the analysis of the complex impact of smart automation technologies on assembly system by considering location factors. The goal is to derive the implementation strategy to achieve the maximum improvement of KPIs. The decision variables are such as improvement rate of significant KPIs. The constraints have been just explained namely total investment of capital and the implementation days of technologies. There are two scenarios considered which are decided by the Beijing plant. In the first scenario, the total investment and the implementation days are relatively sufficient to avoid the infeasible implementation due to the constraints. In the second scenario, the investment budget is limited to 1.5 million RMB and the implementation duration is maximus 1400 days. In this work, the first scenario has been explained in the following. The second scenario has been summarized in Appendix A9. The actual inputs are gathered according to previous sub-Sections of 5.2. Subsequently, all quantities have been specified mathematically. The optimization model is completed and correctness test is conducted.

The collected equations in the optimization model are summarized according to Section 4.5.2. The separate bounds, linear equalities, linear inequalities have been identified. Through the optimization tool (see Figure 5-22) based on Visual Basic for Application©, the optimized sequence is presented as followed (see Table 5-6). The Intelligent screwdriver (INS) and Automatic torque adjustment (ATA) were not considered in the optimization of implementation sequence since they are well implemented in the Beijing plant. The implementation sequence for the remaining 10 of 12 technologies have been optimized.

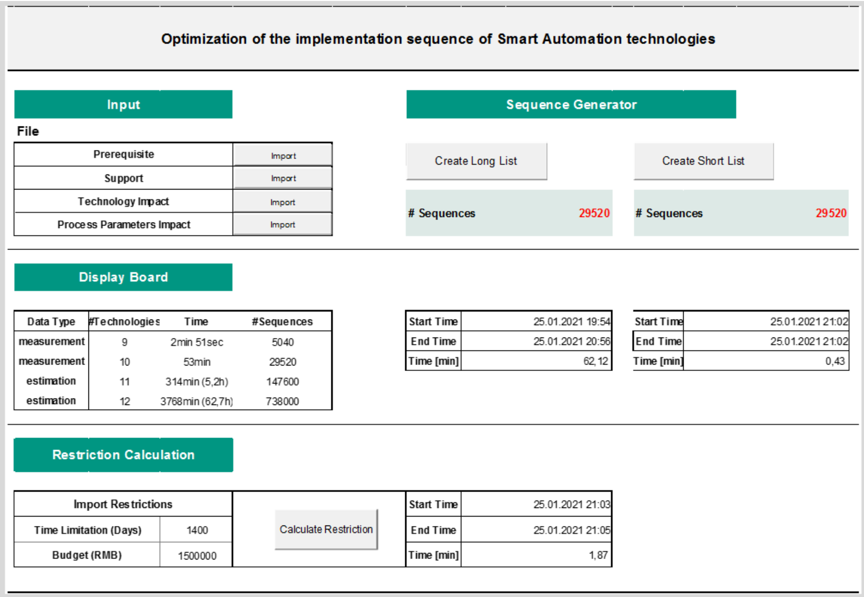


Figure 5-22: The optimization tool of implementation sequence of smart automation technologies

Table 5-6: The ranking (top 5) of implementation sequence of smart automation technologies

i	PBL	HMI	QR	WN	AGV	CPM	WCR	DSFM	MES	SG
1	1	5	3	2	8	10	4	7	6	9
2	1	5	3	2	8	9	4	7	6	10
3	2	5	3	1	8	10	4	7	6	9
4	2	5	3	1	8	9	4	7	6	10
5	1	5	4	2	8	10	3	7	6	9
…	…	…	…	…	…	…	…	…	...	…
Initial sequence	10	5	7	6	1	2	4	8	3	9

Evaluation of implementation Strategy

The results in the form of changes in the key figures are shown in Figure 5-23. At first glance, it can be seen that the reduction in production-time-related costs was achieved much earlier with a coordinated strategy than with the initial strategy (see Figure 5-24). The same applies to improving the availability of the plants. This can be explained, among other things, by the interdependencies between the technologies and the conditional requirements. The most important goal for the industrial company is the improvement of the quality of the manufactured parts. Here, the coordinated strategy shows a final quality rate of 98.2 percent.

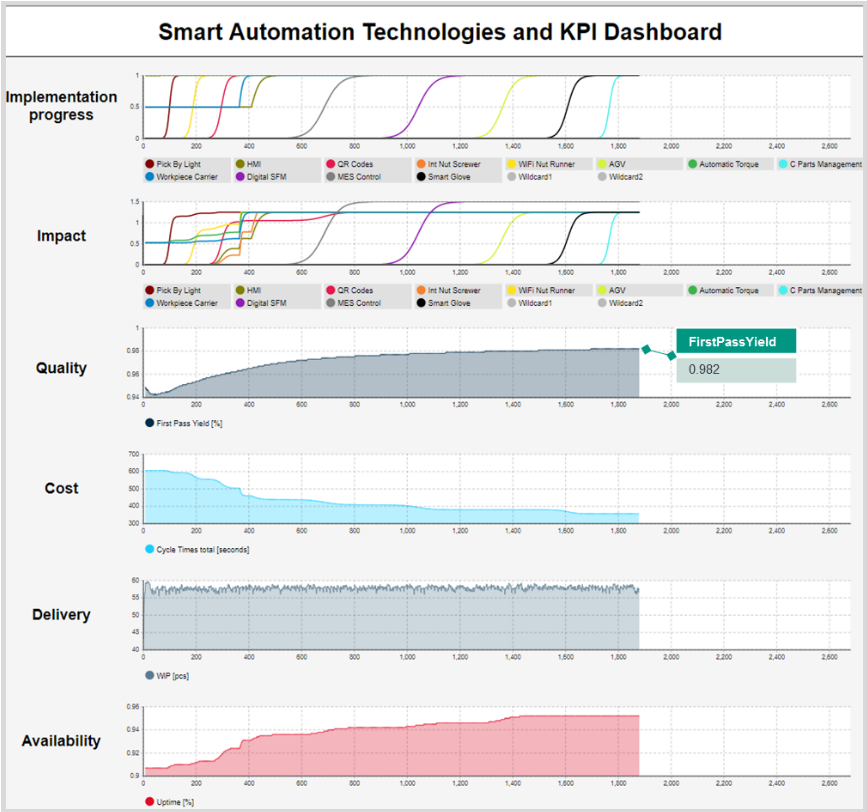


Figure 5-23: The optimal implementation strategy and its impact

The use of the simulation model reveals the advantage of coordinated smart automation strategies in that the advantages of these technologies can be realized at an optimal time and thus significant productivity increases can be made early (see Figure 5-24).

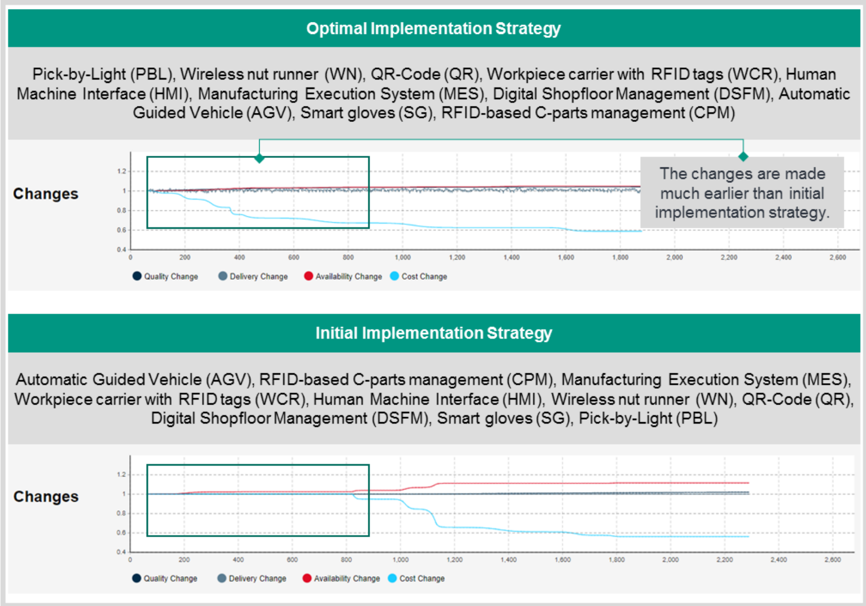


Figure 5-24: The KPIs improvement by optimal- and initial implementation strategy (A_Thiele 2020)

According to Section 4.5.3, the result of Monte-Carlo simulation in a histogram is introduced in Figure 5-25. Since the INS and ATA have been implemented in Beijing Plant, the implementation is starting with PBL at the rank 3. The mean value of the target reach 0.496 which is lower than the optimal value (0.502) in the previous simulation. However, it still shows the relative stable values by differences in expert input if more iterations are conducted.

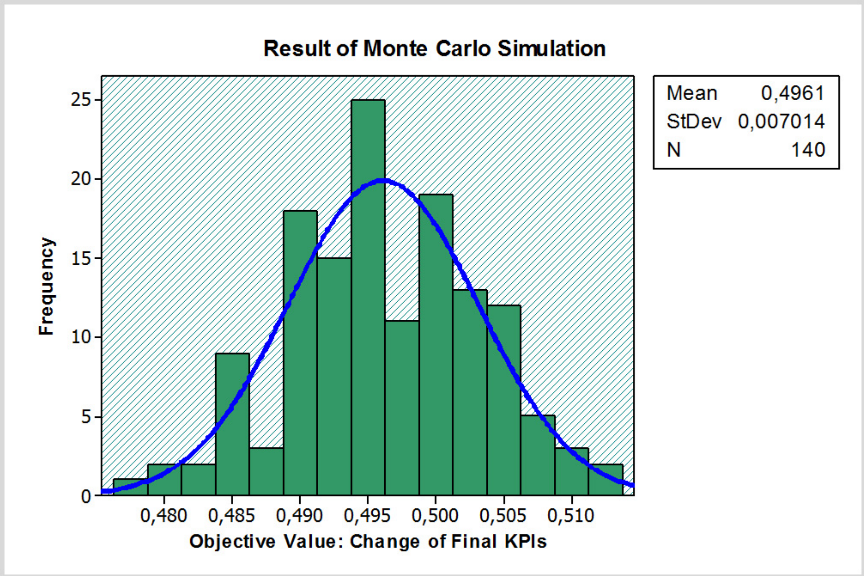


Figure 5-25: The result of Monte-Carlo simulation for optimal implementation strategy

It follows by optimization results that sequence $i = 1$ is the best implementation strategy for the Beijing plant, in terms of key indicators and stability in terms of data. Figure 5-26 illustrates the implementation strategy in a Gantt Chart starting from September of year 2020 and ending in 2026. It is assumed that the technologies are not simultaneously implemented, but only one technology at a time.

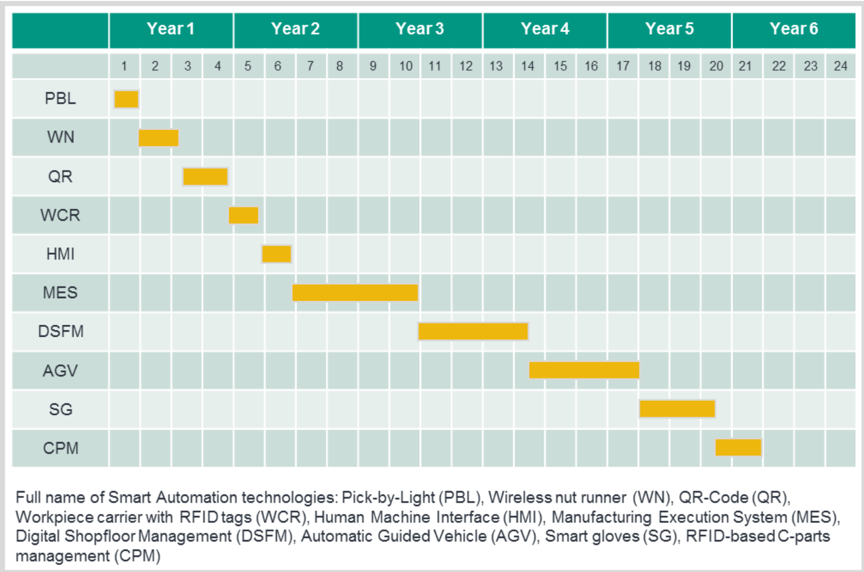


Figure 5-26: Overview of implementation strategy based on Gantt Chart

The implementation can be divided into three phases. The first phase primarily aims at either the implementation of all important prerequisite technologies, or the technologies with strong impact of KPIs without prerequisite technologies. PBL, WN, QR, WCR and HMI are implemented. This phase lasts about one and half years and allows the implementation of various other technologies later on. In the second phase, MES and DSFM is able to be implemented and it takes about almost two years on the one hand. The MES system, on the other hand, must be implemented for a functioning DSFM. Finally, in the third phase, due to the small impact of AGV, SG and CPM, they will only be introduced towards the end.

6 Evaluation and Outlook

Two major aspects are focused on in this section. First, the evaluation of the developed method is illustrated (Section 6.1) and subsequently, the future research is suggested (Section 6.2).

6.1 Evaluation

The proposed approach for developing a regionalized implementation strategy of smart automation within assembly systems applies the qualitative and quantitative analysis for interdependencies among location factors, smart automation and KPIs and derives the optimized implementation strategy enabled by hybrid modeling and simulation. The method is now evaluated according to the requirements defined in Section 3:

1. to take into account the company-specific initial situation such as the relevant location factors and smart automation as well as KPIs
2. to qualitatively and quantitatively calculate the interdependencies among location factors, smart automation and KPIs
3. to derive an implementation strategy of smart automation technologies

The approach accomplished the first requirement by applying a three-step method, namely literature review, questionnaire and expert interview. As a result of an extensive literature research, the long catalog, which consists of location factors, smart automation and KPIs was generated. The catalog was further carried out by prioritizing of long list through 79 useable samples of questionnaire from focused three economic areas of China. The finalized catalog was modified on the basis of expert interviews from the industrial domain. As a consequence, the significant location factors, the enabling technologies of smart automation and important KPIs were identified. These catalogs helped to better understand the corporate environment in the specific country, China in this context.

The second requirement of the research was accomplished by investigating the net of interdependencies among location factors, smart automation and KPIs. The data were gathered from both questionnaire and expert interviews. The correlations were modeled in the qualitative way by positive, neutral and negative influences with different levels, such as strong or weak impact. The qualitative results were further transferred to quantitative results by expert interview, particularly the experts from technology providers and experiments based on testbeds at the GAMI. The former provided the detailed data for smart automation technologies based on their professional knowledge and the latter collected the specific data for the interdependencies between smart automation and KPIs. The data by the experiments were able to reflect real production since the testbed provided a real production environment and demonstrated the enabling technologies in the assembly system sufficiently well. By analysis, the interdependencies among location factors, smart automation and KPIs from experiments, expert interview and questionnaire, the influence mechanisms were worked out, which provided initial input for further modeling and simulation of implementation strategies.

The third requirement of the research was accomplished by hybrid modeling and simulation. System Dynamics (SD) models were used to represent the interdependencies. Since SD models did not take company-specific circumstances into account sufficiently, the modeling of Discrete Event Simulation (DES) was used to model the production system itself. Due to high complexity, the behavior and impact of smart automation technologies were modeled through Agent Based Simulation (ABS). The modular modeling enables production line simulated by means of DES can be simply modified with drag and drop, and three different process curves of technology implementation could be chosen before or during simulation. In addition, the process data such as number of operations, mean time to failure and the initial implementation level of the smart automation technologies were considered in the presented model, which uses process data to describe production systems which provides both systematical and process perspectives. Optimization and evaluation were conducted, which is crucial for derivation of the optimal and robust implementation strategy. Through the optimization, the implementation strategy was tailored to the specific framework conditions customer concerns, which increased the feasibility of implementation.

6.2 Outlook

Although the existence of interdependencies among location factors, smart automation and KPIs were investigated and the derivation of an implementation strategy based on hybrid modeling and simulation was demonstrated, there are still several interesting directions for future research.

First, additional efforts would be also necessary to widen the scope of location factors and smart automation technologies as well as KPIs considered in the analysis of interdependencies. The prototypical smart automation technologies studied are fewer than the number of existing application fields of CPPS and particularly Artificial Intelligence applications in production. Due to new customer values and legislative initiatives, the consideration of environmental and sustainability-related aspects is moving more into the focus of manufacturing companies. An extension of the model to the simulation of the effects of smart automation on the reduction of environmental emissions can create considerable benefits for companies.

Moreover, future research is encouraged to investigate such interdependencies at a more detailed level. For instance, whether a certain location factor affects a smart automation technology only at a certain maturity level can be studied. This would provide valuable knowledge with regard to the problem related to achieving of “perfect” maturity.

Furthermore, the integration of CO2 emissions as one of KPIs in future research is suggested. Additionally, intangible KPIs, such as company image and customer relationships also need to be considered in the future. The customer looks forward to cooperating with the partner, who is engaged to keep continuous improvement by applying the innovative technologies. The implementation of smart automation can bring intangible benefits to the Beijing plant, according to the feedback of experts.

In addition, as the focus of this work was set on highly dynamic emerging countries, in particular, China, additional research will be needed to understand whether the obtained results also hold for highly industrialized countries such as Germany.

Last but not least, the influence regarding the role of factories in term of global production networks could be also addressed for developing regionalized and synergistic implementation strategies as part of future research.

7 Summary

With the concept of Industry 4.0 and the development of economic globalization, digital manufacturing is one of the world's leading production trends to solve the challenge caused of an environment characterized by volatility, uncertainty, complexity and ambiguity (VUCA). The industrial companies, especially small and medium-sized firms in the emerging countries such as China, are eager to increase productivity through enhancing Lean Production through digital technologies. Smart automation is one of promised solutions aiming to take advantage of advanced manufacturing technologies to enable flexibility and improve production performance. However, the companies often cannot implement all technologies of smart automation at the same time under resource constraints, and it is extremely time and cost consuming to find out which smart automation technologies should be given priority to be implemented due to a large amount of variables, such as location factors and influences on specific production systems. Many of the operations that are performed within the company depend strongly on the location factors by considering access to customers, skilled labors, transportation, etc. Therefore, a proper implementation strategy of smart automation by considering influence of location factors is expected.

Through the literature review, the current research approaches only addressed the increase in efficiency by Lean methods and the fields and maturity level of CPPS application. The influence of location factors for implementing smart automation into Lean Production has not been sufficiently considered. Moreover, the investigation on analysis of the interdependencies among location factors and smart automation as well as KPIs is still lacking. Furthermore, it is missing a method to derive the implementation strategy of smart automation technologies for enhancing Lean Production considering those interdependencies.

The objective of this research is to develop regionalized implementation strategy of smart automation within assembly system. The method has to take into account the company-specific initial situation such as the relevant location factors. The interdependencies among location factors and smart automation as well as KPIs need to be figured out. The regionalized implementation strategy is to be derived to improve the KPIs.

In the first part, the specific location factors, smart automation technologies and KPIs, which are important for China as dynamically developing country, were identified and merged together based on the literature review, questionnaires and expert interviews.

In the second part, qualitative and quantitative analysis of interdependencies were conducted to determine the net of impact among location factors, smart automation and KPIs by experiments in a testbed at the GAMI and expert interviews of technology providers. In the third part, the interdependencies were transferred to the company specific assembly system based on hybrid modeling and simulation. Subsequently, in the fourth part, the regionalized implementation strategy was derived based on the specific conditions of the industrial companies with support by optimization and Monte Carlo evaluation. The methodology was developed in the framework of the Sino-German research project I4TP ("Sino German Industry 4.0 Factory Automation Platform") which is supported by the German Federal Ministry of Education and Research (BMBF). The validation was successfully conducted with an industrial company in Beijing.

The leading research questions and requirements have been generally considered, nevertheless, there are still some potentials which need to be further studied in so that the methodology is able to meet the requirements of the future.

The developed methodology introduces a novel approach to make decision support by developing the regionalized implementation strategy of smart automation within assembly systems. By applying this methodology the industrial companies are able to effectively derive the tailored implementation sequence of disruptive technologies based on scientifical and rational analysis.

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Appendix

A1 Theory of Reliability and Validity of Survey

To confirm the effectiveness of the designed questionnaire, its reliability and validity has to be examined. If a measuring instrument delivers measurement results that are as identical as possible after repeated use under constant conditions, this means high accuracy. The extent of this accuracy is called the reliability (Dreier 1994). Usually the internal consistency of a test is used to indicate the level of confidence in the test (Chai 2010), the reliability of the test is affected by random errors. In general, the more constant the result of two tests, the smaller the error rate and the higher reliability of the test. Therefore, reliability describes the quality of measurement (Trochim 2006[1]).

Taking into account the practical functioning of the retest reliability law and its limitations, the Cronbach's Alpha methods with the help of the Statistical Package for the Social Science (SPSS) software are used to check the reliability of the questionnaire. The following Table 0-1 evaluates the result using the rule of thumb to interpret the alpha values (George & Mallery 2003).

Table 0-1: Rule of thumb for interpreting the alpha values (George & Mallery 2003)

α	Meaning
>0,9	Excellent
>0,8	Good
>0,7	Acceptable
>0,6	Questionable
>0,5	Bad
<=0,5	Unacceptable

The validity of a measurement is given when an empirical measurement matches a logical measurement concept, the validity describes the degree of this agreement (Lienert & Raatz 1998). The purpose of the questionnaire is to get meaningful and exact measurements and conclusions. The higher validity indicates that the result of the questionnaire can represent the higher degree of truth of the test to be carried out. More goals of the questionnaire are achieved, the more correct and effective the questionnaire will be. There are two types of validity. One of them is the content validity, which

[1]Trochim, W. M. (2006), "Types of reliability. Research methods knowledge base" Conjoint.ly. http://www.socialresearchmethods.net/kb/reltypes.php [07.06.2020].

is checked by expert interviews in the later sub-Section. The other is construct validity, which is checked by factor analysis in SPSS (Chai 2010). In order to carry out the factor analysis, the Bartlett test for sphericity is first carried out to determine the Kaiser-Meyer-Olkin (KMO) value. The KMO value provides information about the quality of the factor analysis, as can be seen from the following Table 0-2.

Table 0-2: Evaluation of quality of the factor analysis

KMO value	Suitability of the data for factor analysis
>0,9	Very good
0,8-0,9	Good
0,7-0,79	Medium
0,6-0,69	Pass
0,5-0,59	Bad
<0,5	Not suitable for factor analysis

If the KMO value is greater than 0.6 and the result of the Bartlett test for sphericity $p<0.05$, this means that the data are suitable for a factor analysis. Then the factor analysis is carried out to check the validity of the questionnaire.

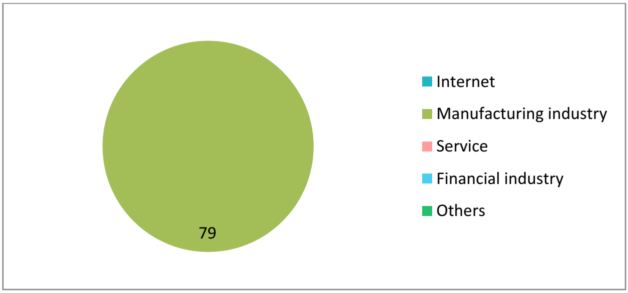
Additionally, if a measure´s scores are unreliable, it is difficult to know whether they have results meriting further investigation. The Cronbach´s Alpha provides a measure of the internal consistency of a test or scale. It is expressed as a number between 0 and 1. Internal consistency describes the extent to which all the items in a test measure the same concept or construct and hence it is connected to the inter-relatedness of the items within the test.

A2 The Questionnaire and Results of Location Factors

Questionnaire survey

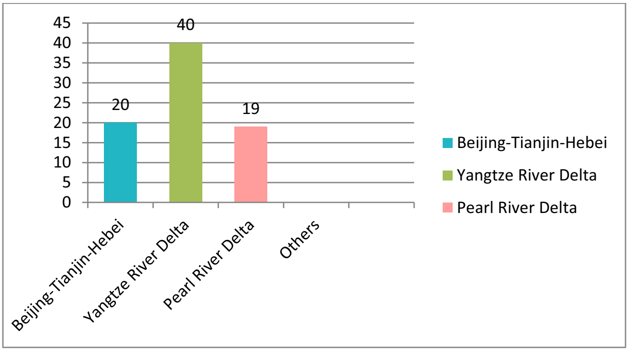
1. your working area is? 您从事的行业领域 (单选题 *必答)

○ Internet 互联网
○ Manufacturing 制造业
○ Service 服务业
○ Finance 金融业
○ Other 其他



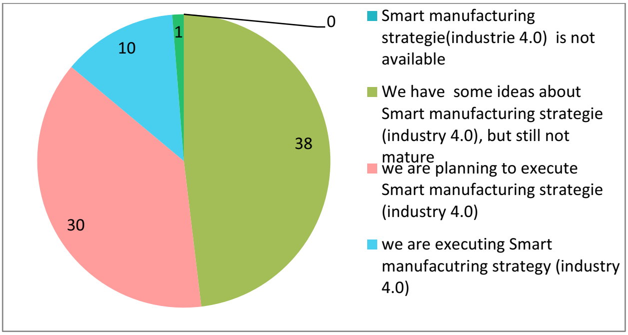
2. location of your company? 您公司的地理位置位于？(单选题 *必答)

○ Beijing-Tianjin-Hebei 京津冀
○ Yangtze River Delta 长三角
○ Pearl River Delta 珠三角
○ Southwest 西南地区
○ Others 其他



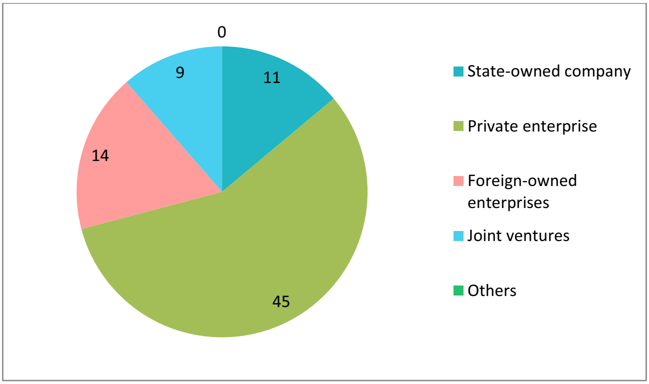
3. How do you evaluate the degree of implementation regarding smart manufacturing (or Industry 4.0) in your company? 您如何评价贵公司智能制造（或工业 4.0）的实施程度？(单选题 *必答)

○ Smart manufacturing strategy (industry 4.0) is not available 没有战略
○ We have some ideas about smart manufacturing (industry 4.0), but still not mature 已经有一些初步的想法，但未形成系统战略
○ We are planning to execute smart manufacturing strategy (industry 4.0) 已经着手进行智能制造（工业 4.0）战略
○ We are executing smart manufacturing strategy (industry 4.0) 正在实行智能制造（工业 4.0）战略中
○ Strategy is already achieved 智能制造（工业 4.0）战略已经实施



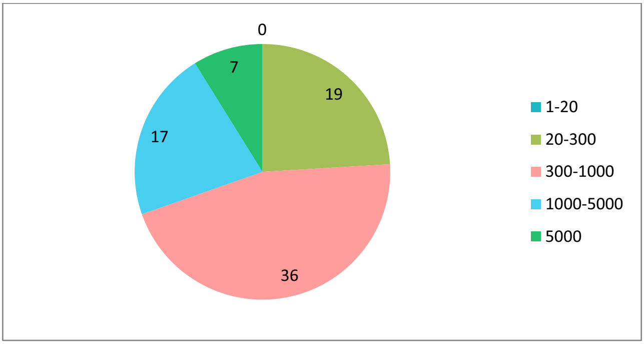
4. In which sort of company do you work? 公司类型？(单选题 *必答)

○ State-owned enterprise 国有企业
○ Private enterprise 私营企业
○ Wholly foreign-owned enterprise 外企独资企业
○ Joint ventures 中外合资企业
○ Other 其他



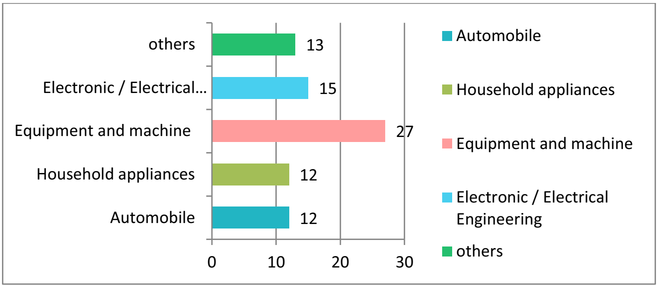
5. How many employees does your company have? 员工人数？(单选题 *必答)

○ 1-20
○ 20-300
○ 300-1000
○ 1000-5000
○ 5000



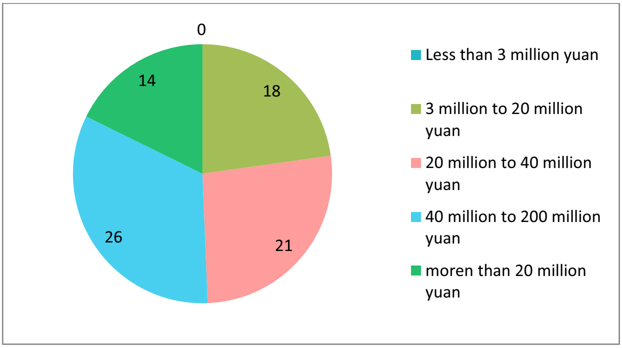
6. Which industrial sector does your company mainly belong to? 公司行业？(单选题 *必答)

○ Automotive industry 汽车业
○ Home appliances 家用电器
○ Machinery and equipment building 设备仪器和机床
○ Electronics / electrical engineering 电子/电气工程
○ Other 其他



7. Please estimate your company's annual turnover. 公司年营业额？(单选题 *必答)

○ Less than 3 million CNY 小于 300 万人民币
○ 3million to under 20 million CNY 300 万人民币至 2000 万人民币
○ 20 million to under 40 million CNY 2000 万人民币至 4000 万人民币
○ 40 million than 200 million CNY 4000 万人民币到 2 亿人民币
○ More than 200 million CNY 超过 2 亿人民币

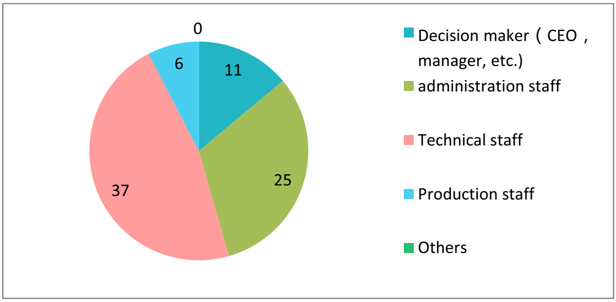


8. What type of products are designed / produced by your company? 公司主要产品？ (单选题 *必答)

○ Industrial products (e.g. equipment, components, materials) 工业产品（例如设备，零部件及材料）
○ Mass consumption products (e.g. automobile) 大众消费类产品（包含汽车）
○ Other 其他

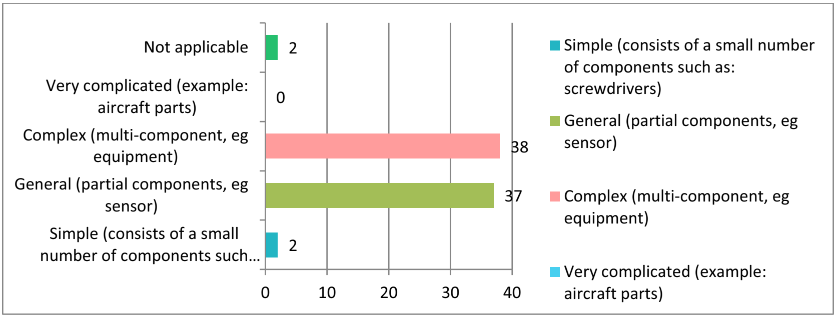
9. In which position are you now? 在职岗位？ (单选题 *必答)

○ Decision maker (CEO，CFO，GM…) 决策层（CEO，董事，经理等）
○ Admin. 行政人员
○ Technical specialist 技术人员
○ Production 生产人员
○ Other 其他



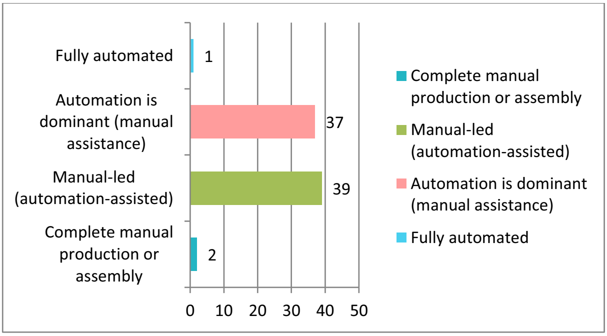
10. According to the number of components, please assess the complexity of the products designed/ produced by your company. 依据零部件数量，公司产品的复杂程度如何？ (单选题 *必答)

○ Simple(few components, e.g. corkscrew) 简单 （少量零部件组成，例如：螺丝锥）
○ General (a few components, e.g. sensors) 一般（部分零部件组成，例如：传感器）
○ Complex (multiple components, e.g. appliances) 复杂（多部件组成，例如：设备）
○ Very complex (many components, e.g. airplanes) 非常复杂 （例如：飞机部件）
○ Not applicable 不适用



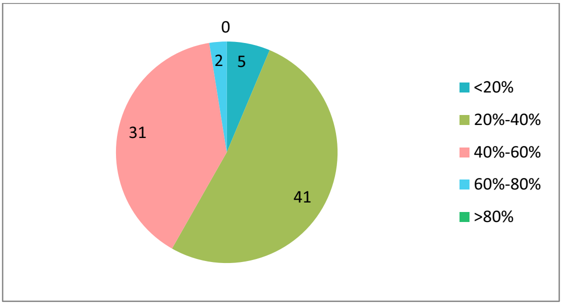
11. Please estimate the level of automation of assembly in your company? 公司装配的自动化程度如何？(单选题 *必答)

○ Completely manual assembly 完全手工生产或装配
○ Predominant manual assembly 手工为主导（自动化辅助）
○ Predominant automated assembly 自动化为主导（手工辅助）
○ Completely automated assembly 完全自动化



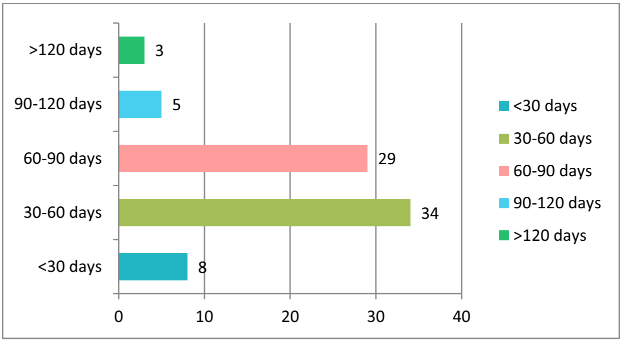
12. What is the proportion of company´s technical staff? 公司技术人员占比为？(单选题 *必答)

○ 15%
○ 15%-25%
○ 25%-35%
○ 35%-45%
○ 45%-55%
○ 55%



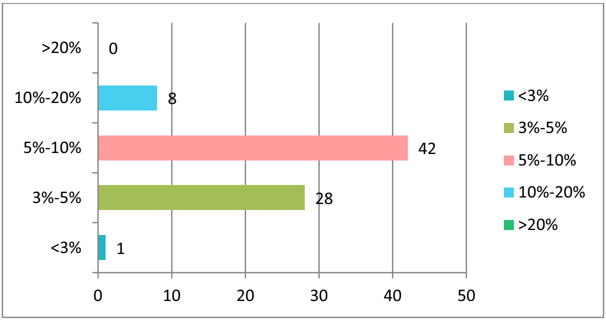
13. How long is the delivery time for the A class product (mainly, select one type)? A 类产品（选最主要的一种）交付期为？(单选题 *必答)

○ 30 天
○ 30-60 天
○ 60-90 天
○ 90-120 天
○ 120 天



14. What is the ratio of equipment maintenance cost to total costs? 设备维修支出占总支出的比例为？(单选题 *必答)

○ 3%
○ 3%-5%
○ 5%-10%
○ 10%-20%
○ 20%

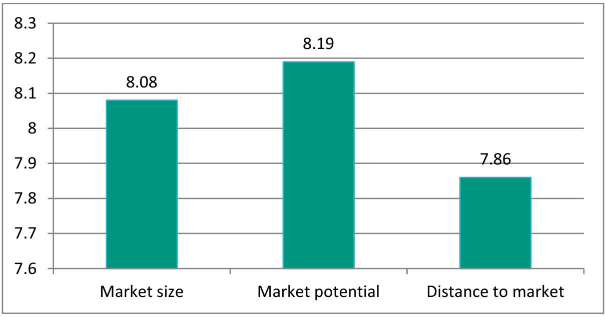


15. HowIs the attention to smart automation or smart factory in your company? 对智能自动化或者智能工厂的关注度如何？ (单选题 *必答)

○ Not interested 完全不关心
○ A little 知道一点
○ Common 一般
○ High 高
○ No idea 我不清楚

16. How important are the following Market related location factors to your company? (1is the least important and 10 is the most important.)：Market. 请评估下列市场相关区位因素的重要程度（1-10 分，1 分-无关系，10 分-非常重要）: 市场 (打分题 请填 1-10 数字打分 *必答)

Market size 市场大小 ______
Market potential 市场潜力 ______
Distance to market 市场距离 ______



17. How important are the following Costs related location factors to your company? (1 is the least important and 10 is the most important.)：Costs. 请评估下列成本相关区位因素的重要程度（1-10 分，1 分-无关系，10 分-非常重要）: 成本 (打分题 请填 1-10 数字打分 *必答)

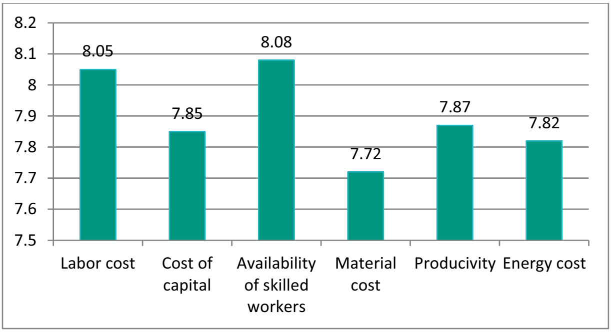
Labor costs 劳动力成本 ______
Cost of capital 资本成本 ______

Availability of skilled workers 技能型人才 _____

Material costs 材料成本 _____

Productivity 生产率 _____

Energy-and other costs 能源成本以及其他成本 _____

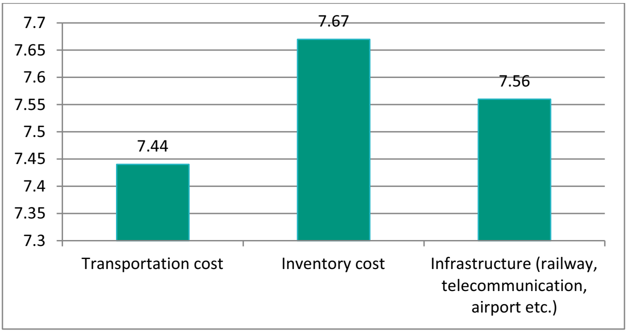


18. How important are the following Logistics related location factors to your company? (1 is the least important and 5 is the most important.)：Logistics. 请评估下列物流相关区位因素的重要程度（1-5 分，1 分-无关系，5 分-非常重要）: 物流 (打分题 请填 1-5 数字打分 *必答)

Transportation costs 运输成本 _____

Inventory costs 库存成本 _____

Infrastructure (such as railway, airport, roads and telecommunication) 基础设施（如铁路，公路，机场，电信设施等）_____

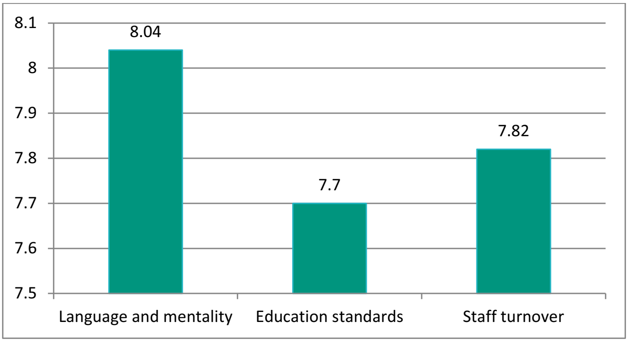


19. How important are the following Culture related location factors to your company? (1 is the least important and 5 is the most important.)：Culture. 请评估下列文化相关区位因素对贵公司的重要程度（1-5 分，1 分-无关系，5 分-非常重要）: 文化 (打分题 请填 1-5 数字打分 *必答)

Language and mentality 语言及思维方式 _____

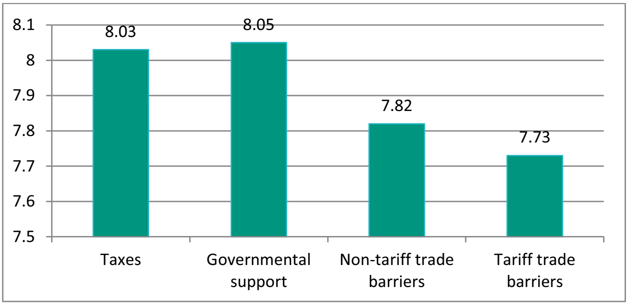
Education standards 教育水平 _____

Staff turnover 员工流动率 _____



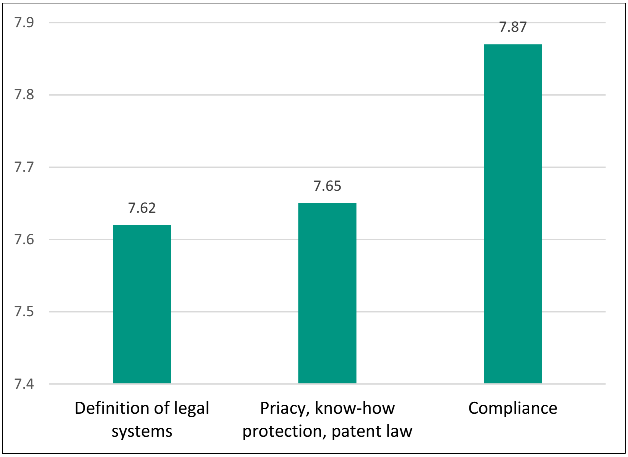
20. How important are the following Politics and Government related location factors to your company? (1 is the least important and 5 is the most important.)：Political and governmental factor. 请评估下列政治和政府相关区位因素的重要程度（1-5 分，1 分-无关系，5 分-非常重要）: 政治和政府因素 (打分题 请填 1-5 数字打分 *必答)

Taxes 税率 _____
Governmental support 政府支持 _____
Non-tariff trade barriers-local content 非关税贸易壁垒 _____
Trade barriers-duties 关税贸易壁垒 _____



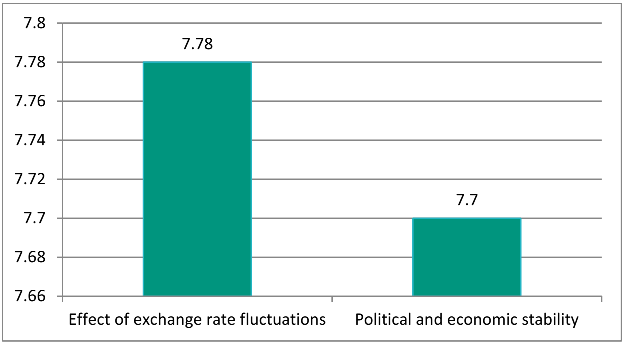
21. How important are the following Legal related location factors to your company? (1 is the least important and 5 is the most important.)：Legal factor. 请评估下列法律区位因素的重要程度（1-5 分，1 分-无关系，5 分-非常重要）: 法律因素 (打分题 请填 1-5 数字打分 *必答)

Definition of legal systems 法律体系的定义（如大陆法系，英美法系，社会主义法系） _____
Piracy, know-how protection, patent law 盗版，专有技术保护，专利法 _____
Importance of legal compliance 合规 _____



22. How important are the following Risks related location factors to your company? (1 is the least important and 5 is the most important.)：Risks. 请评估下列风险因素对贵公司的重要程度（1-5 分，1 分-无关系，5 分-非常重要）: 风险 (打分题 请填 1-5 数字打分 *必答)

Effects of exchange rate fluctuation 汇率波动的影响 ______
Political and economic stability 政治及经济稳定性 ______



23. Please rank the following location factors in the order of importance.（1-7, from strong influence to weak influence）请按照重要程度对下列影响因素进行排序（顺位 1-7，由强到弱） (排序题 请填 1-7 数字排序 *必答)

______Market 市场因素
______Factor costs 成本因素
______Logistics 物流因素
______Culture factors 文化因素
______Political and governmental factors 政治政府因素
______Legal factors 法律因素
______Risks 风险因素

	1. place	2. place	3. place	4. place	5. place	6. place	7. place	Average position
Factor market	35	22	11	5	2	4	0	2.10
Factor costs	25	27	12	8	4	1	2	2.37
Factor logistics	6	13	13	10	15	16	6	4.10
Factor culture	4	9	12	15	9	12	18	4.57
Political and governmental factors	8	5	12	15	22	10	7	4.22
Legal factors	1	2	8	15	18	20	15	5.11
Factor risks	0	1	11	11	9	16	31	5.53
Number of respondents	79							

A3 Description of the Generated Application Fields of CPPS

Table 0-3: Description of the generated application fields of CPPS

Application field of CPPS		Description
Manufacturing process	Plug-and-Work	Capability to flexibly adapt production systems to changing requirements by adding or removing individual modules without changing the design of the remaining production system (Vogel-Heuser & Hess 2016)
	Simulation-based control of production processes	Capability to create simulation models and virtual plant models by creating a virtual copy of the physical world including their characteristics, functionalities, behavior, etc. (Wang & Wang 2016)
	Context awareness	Capability of objects (e.g. machines, other facilities and equipment) to “actively” participate in processes (e.g. recognition, analysis, interpretation of plans and intentions of objects, knowledge about own situation, status and options for action) (Monostori 2014)

	Flexibility (batch size one)	Capability of manufacturing of small batch sizes in a cost-efficient way (i.e. mass customization) (Olhager 1993)
	Human-machine interaction	Capability of interaction/ collaboration between humans and objects (e.g. machines, other facilities and equipment) (Gorecky & Schmitt et al. 2014)
	Individualization	Capability of manufacturing of fully customized products, i.e. according to individual customer requirements (Koren & Shpitalni et al. 2015)
	Integration (vertical/ horizontal)	• Horizontal integration: capability to integrate various systems or business planning processes including the exchange of materials, energy and information both within a company or between different business units in the manufacturing network (Liu & Chen et al. 2015) • Vertical integration: capability to integrate various systems at different hierarchical levels (e.g. production management, manufacturing and execution, planning) (Liu & Chen et al. 2015)
	Machine-to-machine	Capability of machines or other facilities to communicate/ interact/ cooperate with each other (Kim & Lee et al. 2014)
	AGV	The use of automated guided vehicles (AGV) for the support or execution of tasks such as transport of materials, weightlifting, etc. (Vis 2006)
	Predictive maintenance	Capability to generate forecasts with regard to the condition of objects (e.g. machines, other facilities and equipment) using previously identified patterns (Schuh & Stich et al. 2017)
	Real-time data based quality management	Capability to perform quality-related tasks (e.g. KPI tracking, estimation of deviations) based on real-time data (Oks & Fritzsche et al. 2017)
	Self-X (self-configure, self-aware, self-predict, self-compare, self- organize)	Capability of objects (e.g. machines, other facilities and equipment) to autonomously (i.e. without intervention) execute actions/ tasks or make decisions depending on the analysis of various data (e.g. considering their current state, environment, etc.) (Onori & Semere et al. 2011)
	Virtualization (Augmented reality/ Virtual reality)	The application of augmented reality (e.g. sending repair instructions over mobile devices)/ virtual reality (e.g. virtual prototyping, web-based virtual machining, fault diagnosis, etc.) in production (Demartini & Tonelli et al. 2017)
Big Data, Cloud	Cloud manufacturing	The use of manufacturing services from the cloud (e.g. Design as a Service, Manufacturing as a Service (MFaaS), Experimentation as a Service (EaaS), Simulation as a Service (SIMaaS), Management as a Service (MANaaS), Maintain as a Service (MAaaS), Integration as a Service (INTaaS)) (Zhang & Luo et al. 2014)
	Data analytics	Capability of analyzing (huge amounts of) data using advanced data analytics methods and extracting valuable knowledge from it (Elgendy & Elragal 2014)
	Real-time capability	Capability of objects (e.g. machines, other facilities and equipment) to immediately use/ analyze data and to adapt in time to unpredicted circumstances (Smit & Kreutzer et al. 2016)stark
	Servitization	Capability to provide services via the internet, based on a service oriented reference architecture (SOA) (Vogel-Heuser, et al., 2016)

Information and Computing Technology (ICT)	Automated data processing	Capability to automatically gather/ process data (Yamashita & Hirata et al. 2018)
	Intelligent networking	Interconnection and interaction between objects (e.g. machines, other facilities and equipment) with "smart" capabilities (e.g. context awareness, self-x, etc.) as well as with humans using standardized interfaces (Siepmann & Graef 2016)
	Intelligent production management	Capability to ensure automated and optimal influx of production material and other resources into production processes based on the analysis of multiple data from both past and current planning periods (e.g. performance-related data, current outstanding orders, potential future orders, capacity utilization, etc.) (Oks & Fritzsche et al. 2017)
Research and Development	Intelligent product development	Capability to integrate data from individual life cycle of products into the product development (e.g. by integrating sensors for data acquisition in products) (Oks & Fritzsche et al. 2017)
Logistics and SCM	Automated e-procurement	Capability to automatically perform tasks, such as calculation of optimal order quantity, based on both internal data (e.g. real-time data from production, warehousing, incoming orders) and external data (e.g. market trends and price developments) (Oks & Fritzsche et al. 2017)
	Automated warehousing	Capability to automatically execute tasks such as transport of materials, weightlifting and warehousing (e.g. by the use of AGV or other technical solutions) (Wang & McIntosh et al. 2010)
	Autonomous logistics subsystems (transport, order processing, turnover handlings)	The use of objects or systems with "smart" capabilities (e.g. context awareness, self-x, etc.) in logistics processes such as transport, order processing, turnover handlings (Timm & Lorig 2015)
	Digital/ virtual picking	The application of digital solutions for augmented reality/ virtual reality (e.g. selecting parts using smart glasses) in the order picking (Demartini & Tonelli et al. 2017)
	Integration of supply chain	Capability to integrate and optimize various systems or business planning processes including the exchange of materials and information along the entire supply chain network (Flynn & Huo et al. 2010)
	Intelligent material labeling	Digital labeling of material or carriers which allows for communication with other logistics and production resources and autonomously transmitting information considering their state and location (Digital in NRW)
	Real-time localization and tracking	Capability to track and localize transport units in real-time (Ratosi & Simon 2018)
	Simulation-based control of supply chain	Capability to create simulation models and virtual supply chain models by creating a virtual copy of the physical world including all parties involved, their characteristics, functionalities, behavior, etc. (Wang & Wang 2016)

A4 Description of Smart Automation

Pick-by-Light (PBL)	
Picture	**Description**
	With several product variants to be produced in one assembly line, the Pick by Light at specific working stations helps operators to pick the correct components for different variants. Based on the information from MES system to identify the current under-processing product variant, LED lamps will give green(for correct operation) / red(for wrong operation) signals when the operator choose one of the bins to pick components.
Category	**Benefits**
Transparency	▪ Reduction of defect ratio ▪ Reduction of quality cost ▪ Increase of productivity

Human Machine Interface (HMI)	
Picture	**Description**
	At each working station on the GAMI assembly line, a all-in-one machine shows step-by-step work instructions of the station dynamically, according to different product variants, in video form for the operators. This friendly human-machine interface assisted the workers to operate correctly and quickly and to save time from finding and reading paper working instructions.
Category	**Benefits**
Human Machine Interaction	▪ Reduction of defect ratio ▪ Reduction of quality cost ▪ Increase of productivity

QR-Code (QR)			
Picture	**Description**		
	Compared to traditional 1D bar code, QR code can store a great deal more essential product information both horizontally and vertically. It can provide a wealth of details, including the condition of the product, the date of production, accurate delivery time data and full traceability. Applied in inventory systems, manufacturer can monitor the inventory levels, build assemblies according to the bill of materials, track the manufacturing processes and collect real time data. Information collected is sent to a secure, central cloud location and can be instantly available to all authorized users.		
Category	**Benefits**		
Real-time Decision Support	▪ Increase of traceability	▪ Real-time data collection	▪ In crease of productivity

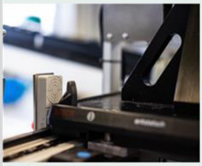
Intelligent screwdrivers (INS)			
Picture	**Description**		
	The screwdrivers matched with different types of tool heads are useful for multi-varieties and small-batch production . Controlled by pre-defined process programs, the screwdrivers on GAMI assembly line lock themselves when the processing steps are finished at each station to prevent faulty operations. In addition, the screwdrivers could send important process data to local devices, where the real-time data will be automatically analyzed and visualized to show process anomalies.		
Category	**Benefits**		
Human Machine Interaction	▪ Reduction of defect ratio	▪ Reduction of quality cost	▪ Reduction of time for data collection

Wireless nut runner (WN)			
Picture	**Description**		
	A Wireless nut runner (e.g. Bosch Nexo) features a fully integrated logic controller, which monitors all the torque and rotation angle of the tightening action. These process data are displayed instantly to let the user know if the tightening has been successful along with other key information. In addition, the data are sent wirelessly to local devices or a cloud platform, where the real-time data will be automatically analyzed and visualized to show process anomalies.		
Category	**Benefits**		
Changeability and Flexibility	▪ Process reliability	▪ High-precision measurement	▪ Rapid information availability

Automatic Guided Vehicle (AGV)			
Picture	**Description**		
	An automated guided vehicle (AGV) is a portable robot that follows markers or wires in the floor, or uses vision, magnets, or lasers for navigation. They are most often used in industrial applications to move materials around a manufacturing facility or warehouse. The AGV in innovation center uses color tape for guidance and can attach trailer behind it and tow raw materials or finished products. It is also equipped with a bumper sensor as a failsafe. With remote control via Wi-Fi and high battery capacity, the AGV provides reliable transportation services for intralogistics.		
Category	**Benefits**		
Changeability and Flexibility	▪ Reduction of the number of employees	▪ Increase of productivity	▪ Increase of transport security

Automatic torque adjustment (ATA)			
Picture	**Description**		
	The wireless nut runner and intelligent screwdriver are both applied with automatic torque adjustment function. Not only the modular construction of the tightening spindles enables a very precise adjustment to the tightening task, but also the torque and angle of turn are measured as close as possible to the screw (no gearbox between measurement transducer and screw). In addition, wireless nut runner, the intelligent screwdriver and other integrated tightening systems can be connected with integrated logic.		
Category	**Benefits**		
Connectivity	▪ Increase of connectivity	▪ Increase of productivity	▪ Reduction of defect ratio

RFID-based C-parts management (CPM)			
Picture	**Description**		
	The RFID-based C-parts management (e.g. iBox system) consists of the iBox and corresponding bins. It is based on the principle of the Kanban system, which provides C-Parts "just-in-time" directly at the point of use. Each bin has a barcoded Kanban label and RFID tag which specifies the customer, storage location, item, etc. in details. When the parts in a bin are used up, the operator should place the empty bin in the iBox and close it. Afterwards the RFID reader inside the iBox will read the RFID tag and forward all the information to the supplying position. Each bin movement is captured and documented automatically, so that information about the status of Kanban system is accessible at any time.		
Category	**Benefits**		
Connectivity	▪ Higher supply security	▪ Simplification of data transfer and order transfer	▪ Integration of process

Workpiece carrier with RFID tags (WCR)			
Picture	**Description**		
	The RFID identification system enables targeted workpiece pallet control to the corresponding workstations. It ensures the flow of information accompanying goods in the assembly lines. Object-related data enable the targeted control of process and processing steps, as well as the type- or variant-dependent inward and outward transfer of workpiece pallets during the production of product variants on branched, flexible assembly systems. By documenting all process steps and production data, traceability when errors occur is also possible.		
Category	**Benefits**		
Real-time Decision Support	▪ Increase of traceability	▪ Real-time data collection	▪ In crease of productivity

Digital Shopfloor Management (DSFM)	
Picture	**Description**
	The ActiveCockpit is an intelligent dynamic shopfloor management system with clear interface and real-time presentation of production data, which can help users to make quick decision and communicate effectively. It is able to collect, analyze and visualize manufacturing data in real time. In doing so, IT applications such as production planning, quality data management and email dispatch are connected with software functions from machines and systems.
Category	**Benefits**
Transparency	▪ Acceleration of decision-making ▪ Increase of transparency ▪ Increase of productivity

Manufacturing Execution System (MES)	
Picture	**Description**
	Manufacturing Execution System is computerized system used in manufacturing to connect, monitor, and tightly control the manufacturing operations.
Category	**Benefits**
Analytics and Intelligence	▪ Access real-time information ▪ Increase in reliability ▪ Increase in traceability

Smart gloves (SG)	
Picture	**Description**
	The Smart gloves (e.g. Bosch Intelligent Glove) show a method to collect required data from manual working more efficiently. It consists of classical fabric glove and electronics with Bluetooth, which allows plug-play in multiple environment and is integrated with MEMS (Micro Electro Mechanical System Units) that detect and capture real time 3D data from each finger. It then uses innovative algorithms to translate the data into precise gesture commands. And it's also able to collect operation data fully automated (e.g. cycle time, operator occupation rate). Using sensor technology, BIG traces continuous hand motion and transmits them in real-time for use in tracking, training, or even safety audits.
Category	**Benefits**
Analytics and Intelligence	▪ Reduction of process time ▪ Reduction of training time ▪ Increase of process safety

A5 Investigation of KPIs

AWF (https://www.awf.de/wp-content/uploads/2014/12/Kennzahlen-in-der-Produktion-awf.pdf) states that KPIs regarding production can be chosen or defined very differently according to the target of a company. Usually, the important indicators of production can be divided into seven categories: Personnel, Time, Costs, Quality, Flexibility of Organization, Logistics and Environment, each with several sub-elements (see Figure 0-1).

Indicators of Production						
Personnel	**Time**	**Costs**	**Quality**	**Flexibility of Organization**	**Logistics**	**Environment**
Absenteeism	Cycle time	Quality costs	Reclamations	Qualification	Costs	Energy
Employee satisfaction	Adherence to schedules	Inventory	Adherence to schedules	Working time	Personnel	Input materials
Order and cleanliness	Level of organization	Storage costs	Process security	Work organization	Quality	Standards/Laws
Flexibility of employees	Material availability	Personnel costs	Machine availability	Processes / methods	Time	Process quality
Communication of information	Processing change management	Production costs	Reaction speed	Innovations	Flexibility	Burdens
CIP	Flexibility (personnel, machine)	Maintenance costs	Customer satisfaction	(Third-Party) Material	Procurement	Costs
Work organisation	Capacity utilization	Overhead costs	Problem solving ability	Capital		
			Material			
			Formal quality			

Figure 0-1: Indicators of production

Continental Tire in Germany

Key-Performance-Indicators (KPIs)

Overview of tire manufacturing plant in Korbach

Production	• Quantity / Volume • Effectivity/Productivity • Total effective equipment performance (TEEP)

Quality Management	• Quality indicators
	  • Waste
	  • Complaint

Maintenance	• Repair / Maintanence / Tire cost
Logistics	• Turn rates • Size achievement
Human Resource	• Variable Headcounts / Fixed Headcounts • Sickness rate • Work accident
Finance	• Convension cost

Figure 0-2: KPIs of Continental Tire Germany (Salokat 2012)

Case study in China

Manufacturing performance indicators

Quality	• Reject rate • Customer complaints
Delivery Time	• On time delivery ratio- OTD
Productivity	• Productivity
Throughput	• Output per month / planned annual output *100%
Inventory	• Inventory • Inventory of semi-finished product

Figure 0-3: KPIs of Huihong in Nantong (in Yangtze Delta Zone)

A6 Ranking of KPIs by Importance

Table 0-4: Ranking of KPIs by Importance according to the questionnaire

KPIs	1	2	3	4	5	6	7	8	9	10	Avg.
OEE	0	0	0	0	1	6	12	33	18	9	8.11
Material availability	0	0	0	2	1	5	14	22	26	9	8.11
ROI	0	0	0	1	1	9	12	23	21	12	8.10
Reaction speed	0	0	0	0	0	8	12	31	21	7	8.09
Lead time	0	0	0	2	3	3	13	29	16	13	8.08
Cost	0	0	0	1	2	7	11	22	32	4	8.06
Customer satisfaction	0	0	0	1	2	3	18	28	17	10	8.04
Revenue	0	0	0	0	2	6	16	23	27	5	8.04
Productivity	0	0	0	0	4	6	15	18	31	5	8.03
Transparency	0	0	0	0	1	6	18	27	21	6	8.00
Flexibility	0	0	1	0	2	5	21	21	23	6	7.91
Machine availability	0	0	0	0	5	5	16	30	18	5	7.84
OLE	0	0	0	1	1	9	18	28	19	3	7.77
Net income cashflow	0	0	0	1	2	11	16	27	16	6	7.75
Set-up time	0	0	1	2	2	8	22	30	13	1	7.47
Scrap rate	0	1	1	3	1	15	13	24	15	6	7.47

A7 Interdependency among Different Smart Automation Technologies

		Vertical to Horizontal	B: Comparable Matrix - Enabling Technology ↓											
			T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
No.	Ab.	Enabling Technology ↓	PBL	HMI	QR	INS	WN	AGV	ATA	CPM	WCR	DSFM	MES	SG
1	T1	Pick-by-Light (PBL)		0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,25	0,25	0,00
2	T2	Human Machine Interface (HMI)	0,25		0,00	0,00	0,00	0,25	0,00	0,00	0,00	0,25	0,00	0,75
3	T3	QR-Code (QR)	0,25	1,00		0,00	0,75	0,25	0,00	0,25	0,25	0,25	0,25	0,00
4	T4	Intelligent screwdriver (INS)	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,00	0,25	0,25	0,00
5	T5	Wireless nut runner (WN)	0,00	0,00	0,00	0,00		0,00	0,00	0,00	0,00	0,25	0,00	0,00
6	T6	Automatic Guided Vehicle (AGV)	0,00	0,00	0,00	0,00	0,00		0,00	0,75	0,00	0,25	0,75	0,00
7	T7	Automatic torque adjustment (ATA)	0,00	0,00	0,00	0,25	1,00	0,00		0,00	0,00	0,25	0,00	0,00
8	T8	RFID-based C-Parts management (CPM)	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,75	0,75	0,00
9	T9	Workpiece carrier with RFID tags (WCR)	0,25	1,00	0,25	0,00	0,00	0,75	0,00	1,00		0,25	0,25	0,00
10	T10	Digital Shopfloor Management (DSFM)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,00
11	T11	Manufacturing Execution System (MES)	0,25	0,75	0,00	0,25	0,00	0,75	0,25	0,75	0,00	0,25		0,00
12	T12	Smart gloves (SG)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,25	0,00	

Figure 0-4: Expert review result 1

		Vertical to Horizontal	B: Comparable Matrix - Enabling Technology ↓											
			T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
No.	Ab.	Enabling Technology ↓	PBL	HMI	QR	INS	WN	AGV	ATA	CPM	WCR	DSFM	MES	SG
1	T1	Pick-by-Light (PBL)		0,25	0,00	0,25	0,25	0,25	0,00	0,00	0,00	0,75	0,75	0,75
2	T2	Human Machine Interface (HMI)	0,00		0,00	0,75	0,75	0,00	0,00	0,00	0,00	0,75	0,75	0,75
3	T3	QR-Code (QR)	0,00	1,00		1,00	1,00	0,25	0,00	0,25	0,25	0,75	0,75	0,25
4	T4	Intelligent screwdriver (INS)	0,00	0,00	0,00		0,25	0,00	0,75	0,00	0,00	0,75	0,75	0,00
5	T5	Wireless nut runner (WN)	0,00	0,00	0,00	0,25		0,00	0,00	0,00	0,00	0,75	0,75	0,00
6	T6	Automatic Guided Vehicle (AGV)	0,00	0,00	0,00	0,00	0,00		0,00	0,25	0,00	0,75	0,75	0,00
7	T7	Automatic torque adjustment (ATA)	0,00	0,00	0,00	1,00	1,00	0,00		0,00	0,00	0,75	0,75	0,00
8	T8	RFID-based C-Parts management (CPM)	0,00	0,00	0,00	0,00	0,00	0,00	0,00		0,00	0,25	0,25	0,00
9	T9	Workpiece carrier with RFID tags (WCR)	0,00	1,00	0,25	1,00	0,75	0,25	0,00	1,00		0,75	0,75	0,25
10	T10	Digital Shopfloor Management (DSFM)	0,75	0,75	0,75	0,75	0,75	0,75	0,00	0,00	0,00		0,75	0,00
11	T11	Manufacturing Execution System (MES)	0,75	0,75	0,75	0,75	0,75	0,75	0,00	0,00	0,00	0,00		0,00
12	T12	Smart gloves (SG)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	

Figure 0-5: Expert review result 2

		Vertical to Horizontal	B: Comparable Matrix - Enabling Technology ↓											
			T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
No.	Ab.	Enabling Technology ↓	PBL	HMI	QR	INS	WN	AGV	ATA	CPM	WCR	DSFM	MES	SG
1	T1	Pick-by-Light (PBL)			0,00						0,00	0,25	0,25	
2	T2	Human Machine Interface (HMI)			0,00						0,00	0,25	0,75	
3	T3	QR-Code (QR)	0,25	1,00		1,00	1,00	0,25	1,00	0,00	0,00	0,75	0,75	0,00
4	T4	Intelligent screwdriver (INS)			0,00						0,00	0,00	0,25	
5	T5	Wireless nut runner (WN)			0,00						0,00	0,25	0,25	
6	T6	Automatic Guided Vehicle (AGV)			0,00						0,00	0,25	0,75	
7	T7	Automatic torque adjustment (ATA)			0,00						0,00	0,00	0,25	
8	T8	RFID-based C-Parts management (CPM)			0,00						0,00	0,75	0,75	
9	T9	Workpiece carrier with RFID tags (WCR)	0,25	1,00	0,00	1,00	0,75	0,25	1,00	1,00		0,75	0,75	0,00
10	T10	Digital Shopfloor Management (DSFM)	0,25	0,00	0,25	0,00	0,25	0,25	0,00	0,75	0,25		1,00	0,00
11	T11	Manufacturing Execution System (MES)	0,75	0,75	0,25	0,25	0,25	0,75	0,25	0,75	0,25	0,75		0,00
12	T12	Smart gloves (SG)			0,00						0,00	0,00	0,00	

Figure 0-6: Expert review result 3

A8 Result of Experiments in Testbed

Pick-by-Light (PBL)

Process data	Unit	Before: without PBL	After: with PBL	Change Rate
Uptime	%	100	100	-
FPY	%	81,3	87,5	8%
Cycle Time	s	56	55	2,00%
WIP	Pcs	4	4	-

Human Machine Interface (HMI)

Process data	Unit	Before: without HMI	After: with HMI	Change Rate
Uptime	%	99,8	99,8	-
FPY	%	87,5	93,8	7%
Cycle Time	s	61	56	8,00%
WIP	Pcs	-	-	-

QR-Code (QR)

Process data	**Unit**	**Before: without QR**	**After: with QR**	**Change Rate**
Uptime	%	99,8	99,8	-
FPY	%	87,5	93,8	-
Cycle Time	s	61	56	8,00%
WIP	Pcs	4	4	-

Intelligent screwdriver (INS)

Process data	**Unit**	**Before: without INS**	**After: with INS**	**Change Rate**
Uptime	%	100	100	-
FPY	%	81,3	87,5	8%
Cycle Time	s	-	-	-
WIP	Pcs	4	4	-

Automatic Guided Vehicle (AGV)

Process data	**Unit**	**Before: without AGV**	**After: with AGV**	**Change Rate**
Uptime*	%	-	-	10%
FPY	%	-	-	5%
Cycle Time	s	-	-	-
WIP	Pcs	-	-	-

*reference value provided by technology provider

Automatic torque adjustment (ATA)

Process data	**Unit**	**Before: without ATA**	**After: with ATA**	**Change Rate**
Uptime	%	99,6	99,8	-
FPY	%	87,5	93,8	7%
Cycle Time	s	58	56	4,00%
WIP	Pcs	4	4	-

RFID-based C-parts management (CPM)

Process data	**Unit**	**Before: without CPM**	**After: with CPM**	**Change Rate**
Uptime	%	-	-	-
FPY*	%	-	-	5%
Cycle Time	s	-	-	-
WIP*	Pcs	-	-	-

*reference value provided by technology provider

Workpiece carrier with RFID tags (WCR)

Process data	Unit	Before: without WCR	After: with WCR	Change Rate
Uptime	%	99,8	99,8	-
FPY	%	93,8	93,8	-
Cycle Time	s	59	56	5%
WIP	Pcs	4	4	-

Digital Shopfloor Management (DFSM)

Process data	Unit	Before: without DFSM	After: with DFSM	Change Rate
Uptime	%	-	-	-
FPY	%	-	-	-
Cycle Time*	s	1800	600	67%
WIP	Pcs	1	1	0

*Time for data collection

Manufacturing Execution System (MES)

Process data	Unit	Before: without MES	After: with MES	Change Rate
Uptime	%	99,6	99,8	-
FPY	%	93,8	93,8	-
Cycle Time	s	59	56	4%
WIP	Pcs	-	-	-

Smart gloves (SG)

Process data	Unit	Before: without SG	After: with SG	Change Rate
Uptime	%	-	-	-
FPY	%	-	-	-
Cycle Time	s	85,5	35,2	59%
WIP	Pcs	-	-	-

A9 Optimization Result of Implementation Sequence

The constraint condition is implementation time is less than 1400 days and the investment budget is less than 1.5 Million RMB. The top 20 rankings have been summarized in the following. The number marked with blue means that both constraints have been met by implementation this technology. The number marked with red means that the constraint of implementation time has been reached.

Table 0-5: The optimization result with the constraint conditions

i	PBL	HMI	QR	WN	AGV	CPM	WCR	DSFM	MES	SG
1	1	5	3	2	8	10	4	7	6	9
2	1	5	3	2	8	9	4	7	6	10
3	2	5	3	1	8	10	4	7	6	9
4	2	5	3	1	8	9	4	7	6	10
5	1	5	4	2	8	10	3	7	6	9
6	1	5	4	2	8	9	3	7	6	10
7	1	5	2	3	8	10	4	7	6	9
8	1	5	2	3	8	9	4	7	6	10
9	2	5	4	1	8	10	3	7	6	9
10	2	5	4	1	8	9	3	7	6	10
11	1	5	3	2	9	10	4	7	6	8
12	1	5	3	2	9	8	4	7	6	10
13	2	5	3	1	9	10	4	7	6	8
14	3	5	2	1	8	10	4	7	6	9
15	3	5	2	1	8	9	4	7	6	10
16	2	5	3	1	9	8	4	7	6	10
17	1	5	4	2	9	10	3	7	6	8
18	1	5	4	2	9	8	3	7	6	10
19	1	5	2	3	9	10	4	7	6	8
20	2	5	1	3	8	10	4	7	6	9

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