

26th CIRP Life Cycle Engineering (LCE) Conference

Development of a regionalized implementation strategy for smart automation within assembly systems in China

Shun Yang^{a,*}, Justus Schrage^a, Benjamin Haefner^a, Gisela Lanza^a

^awbk Institute of Production Science, Karlsruhe Institute of Technology (KIT), 76131 Karlsruhe, Germany

* Corresponding author. Tel.: +49-721-608-44297; fax: +49-721-608-45005. E-mail address: shun.yang@kit.edu

Abstract

Companies struggle to overcome the difficulties stemming from the dynamic environment of global production due to the specific conditions in different regions. Particularly, insufficient know-how about a regionalized implementation strategy of smart automation (SmAu) technologies is one significant difficulty for enterprises. Thus, developing a key performance indicator (KPI) oriented, regionalized implementation strategy for smart automation technologies is increasingly important. In this context, a new approach is exposed to systematically investigate and identify the interdependencies among location factors, smart automation technologies, and KPIs. Firstly, the environment consisting of location-related factors, KPIs and smart automation technologies is defined in detail. Further, a Catalog quantifies the influence of different regions in China. Secondly, important aspects to model the qualitative and quantitative interdependencies in a multimethod simulation are introduced. Subsequently, an approach to analyze suitable implementation strategies is presented. A case study based on a production line for digitalized production technology is used to validate the proposed approach.

© 2019 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/3.0/>)

Peer-review under responsibility of the scientific committee of the 26th CIRP Life Cycle Engineering (LCE) Conference.

Keywords: Sustainable development; assembly system; smart automation; implementation strategy; location factors

1. Introduction

The digitalization of manufacturing is one of the major production trends taking place worldwide. The key characteristics of this trend differ from region to region. In 2015 the Chinese government presented the strategic plan “Made in China 2025”. The goal is to emphasize a shift in Chinas manufacturing economy from quantity to quality [1]. The operation costs, the lead time and the defect rate in local factories are targeted to decrease by 50% until 2025 [2]. With a labor productivity of only 22,400 USD in the year 2014 and slow improvements [3], the introduction of new technologies is necessary to achieve the ambitious goals. Yang et al. identify smart automation (SmAu) technologies as potential solutions [4], however many companies struggle to define an implementation strategy for these technologies. Therefore, this

article aims to describe a method on how to derive such a strategy by means of multimethod simulation. As the scarcity of resources increases, a rise in productivity requires improvements in resource efficiency [5]. This, an implementation strategy is defined as an implementation sequence of the technologies with maximum resource efficiency. In section 2, the literature is reviewed and the research gap identified. The method and the key findings are described in section 3, before being applied for validation purposes in section 4. Finally, a summary concludes the paper.

2. Literature review

In Germany, the potential of Industry 4.0 solutions has been quantified by many authors. acatech predicts a productivity increase of 30% in the German manufacturing

industry [6]. In China, this potential is expected to be even higher [7]. The definition of SmAu takes this specificity into account and considers Industry 4.0 technologies as well as technologies which have long been established in developed countries like a Manufacturing Execution System (MES) [4]. While many papers address the implementation of these technologies, they usually focus on the advantages of implementation [8], the paradigms for successful implementation [9], the implementation of a single technology [10] or the design of the system infrastructure [11, 12]. In contrast, a holistic approach that deals with the process of planning, transforming and implementing can hardly be found in the common literature [13], a detailed description is still missing [14].

Such comprehensive models exist for lean production methods [15, 16]. They focus on KPIs to derive implementation strategies. Furthermore, Jondral, as well as Aull, consider two types of interdependencies. Lean methods can prerequisite or support the impact of one another [15, 16].

Additionally, Yang et al. consider location factors as an important aspect of the environment of SmAu technologies. The suitability of a technology for a factory strongly depends on its location and local specifics [4]. Hence, it can be concluded that the exploration of an implementation strategy of SmAu technologies, must not only consider interdependencies, but also dependencies with KPIs and location factors. This complexity makes the usage of simple calculation sheets as used in the technology roadmap [14] insufficient. A suitable tool for analyzing systems with such a high degree of complexity is simulation.

In the field of manufacturing simulation, the modeling approaches system dynamics (SD) and discrete event simulation (DES) are mainly established [17]. SD aims to analyze a system on a strategic level. This is done by describing the interactions of two elements with mathematical formulas. The usage of so-called feedback loops having a cumulating or decreasing impact on the interactions help to see long-term developments and, therefore, create transparency [18]. Discrete event simulation, on the other hand, perceives the system less as a whole but rather each element individually. Events at discrete times define the development of the system. Hence, it is usually used to model production lines on an operational or tactical level with each machine as an own element [19]. The combination of SD and DES is a so-called multimethod modeling approach. It aims to create a more holistic view of a system and is said to enable researchers to gain richer and more reliable results [20]. Lee et al. compare different modeling approaches regarding the simulation of supply chains and conclude that multimethod simulation is more capable of modeling the real nature of the system [21]. Concerning how an implementation sequence can be derived, the simulation literature differentiates between optimization and the selection of alternatives [22]. The usage of optimization algorithms in a simulation provides a high level of complexity and is usually linked with higher modeling costs. Hence, it is only recommended if a high payoff is expected [23]. In manufacturing related problems on a strategic level, an approximation of the optimal solution is

usually satisfactory. Swisher et al. describe different ranking and selection approaches for DES applications. They aim to derive indifference zones to show which input combinations are of equal value [24]. Whereas, for multimethod simulation a selection approach can hardly be found in the common literature.

Many authors apply simulation to derive implementation strategies. Jondral uses DES in combination with an evolutionary optimization algorithm to determine the implementation of lean production methods [15]. In the same field, Aull [16], Drombrowski [25] and Peter [26] use SD. Liebrecht [27] applies a similar approach to analyze the implementation of manufacturing systems 4.0 methods with SD. In these publications, company-specifics are mainly considered by adjusting the influence of the methods on the KPIs.

Therefore, the use of multimethod simulation to derive an implementation strategy is unique to the research. It aims to increase the accuracy of the results by simulating the production line itself instead of considering its specifics only with mathematical formulas. Additionally, it can be stated that the consideration of interdependencies between technologies and dependencies with location factors and KPIs is omitted in the research so far.

3. Methodology

Based on the previously derived research gap, a methodology is developed to give guidance to companies in developing countries like China and enable them to define strategies for the implementation of SmAu technologies. Nevertheless, the described modeling and experiment approach can be used by companies in developed countries as well. As DES models work especially well with discrete manufacturing and the data gathering in form of location factors and process data was done in regard to assembly systems. Thus, the focus lies preliminary on assembly systems. At first, location factors, KPIs and the interdependencies of SmAu are described, before a Catalog to gather location related input data is presented. Finally, approaches for multimethod modeling and sequence reduction and selection are explored.

3.1. Interdependencies between location factors, SmAu technologies, and KPIs

The literature review identified three significant elements - location factors, the SmAu technologies themselves and KPIs (see Fig. 1).

Location factors describe the quantitative characteristics of a geographic location and can be determined independently of the company. According to Abele et al., to analyze the efficiency of a location, process factors are required as well. They describe the manufacturing process and the characteristics of the product [28]. Hence, they specifically relate to the company's specifics. For this reason, they are aggregated as the company's profile.

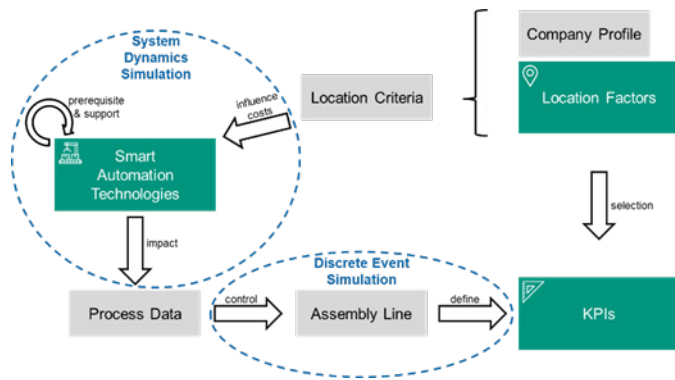


Fig. 1 Interdependencies of location factors, SmAu technologies and KPIs

Only the joint examination of location factors and the company’s profile gives a comprehensive insight into the interaction between SmAu technologies and location. For example, while labor cost is a location factor, required labor time is a company-specific process factor. Accordingly, they are combined into so-called location criteria which determine the efficiency of SmAu technologies for certain locations.

As described previously, the SmAu technologies can be of different nature. Based on the works of Jondral [16] and Aull [17], focusing on the implementation of lean production methods, two types of interdependencies between different technologies are considered. On the one hand, a technology can be a prerequisite to another, which means that until the first technology has been implemented, the dependent technology cannot be used. On the other hand, a technology can support another. This means that the effectiveness or efficiency of the supported technology is improved by the implementation of the other.

Besides the interdependencies, the technologies also influence the production process and thereby indirectly the KPIs. Especially in a manufacturing context the key measures are directly based on data drawn from the production line and used to define the efficiency and effectiveness of the production. A survey, which is presented in the following section, has shown that companies with the same profile focus on different KPIs depending on their location. Thus, a direct correlation between the location and the used KPIs is assumed.

3.2. Catalog of location related input data

After the environment is set up, the input data must be defined. For this purpose, a topology was developed based on Schuh et al. to define company profiles [29]. As foreign-owned companies are of major significance for the Chinese industry, a standard company profile is selected. The following surveys have focused on foreign-owned companies with a semi-autonomous production line, a decent proportion of qualified employees and good coverage of Wi-Fi.

Like Aull [16], a mixture of online surveys and expert interviews was used to collect the data. A list of ten essential location factors was generated based on a survey with 24 company respondents and three expert interviews. The values, in turn, were divided into three levels. Furthermore, three

(Ranking 1-7; 1 as highest priority)	Beijing-Tianjin-Hebei delta	Yangtze River delta	Pearl River delta	Location Factors	Indicator & unit	Level 1	Level 2	Level 3	
QEE	1	2	3	Labor costs	Average annual wage (RMB)	>60,000	1.2 60,000 - 300,000	1.1 >100,000	1
Labor Productivity	2	4	2	Cost of capital	Weighted financing cost (%)	<6%	1.1 6% - 6.5%	1 >6.5%	0.9
Quality Cost	3	1	1	Availability of skilled workers	Staff turnover (%)	low	0.8 medium	0.9 High	1
Customer Satisfaction	4	3	4	Staff turnover	Transport costs/Turnover (%)	<10%	1.2 10%-20%	1.1 >20%	1
Inventory management cost	6	7	7	Transport Costs	Regional raw material cost (bn. RMB)	<500	1.2 500 - 1,000	1.1 >1,000	1
Inventory	5	5	5	Labor productivity		Low	0.8 Medium	0.9 High	1
Efficiency of decision making	7	6	6						

(a) Importance of KPIs per region											(b) Location Factors Typology										
Technologies*	WN	AGV	INS	HMI	ATA	CPM	QR	WCR	PBL	DSFM	MES	SG	correlation								
Labor costs	1.05	1.07	1.00	1.00	1.00	1.05	1.03	1.03	1.00	1.07	1.07	1.00	1.0 none								
Cost of capital	0.90	0.97	0.90	0.95	0.90	0.95	1.00	1.00	0.95	1.00	0.90	0.95	0.92 positive								
Availability of skilled workers	1.10	1.03	1.10	1.10	1.10	1.10	1.03	1.03	1.05	1.07	1.07	1.10	1.03 negative								
Staff turnover	1.05	0.97	0.95	1.10	0.95	1.00	1.00	1.00	1.10	1.07	1.03	1.10									
Transport Costs	1.00	1.00	1.00	1.00	1.00	1.10	1.07	1.03	1.00	1.10	1.03	1.00									
Material Costs	1.05	1.10	1.10	1.05	1.10	1.05	1.10	1.10	1.10	1.07	1.07	1.05									
Labor productivity	1.05	1.00	1.10	1.10	1.05	1.00	1.00	1.00	1.05	1.10	1.10	1.05									
Combi	1.20	1.13	1.14	1.33	1.09	1.27	1.25	1.21	1.27	1.57	1.28	1.27									

Fig. 2 Catalog of location related input data

main regions in China were identified. The Pearl River delta, the Beijing-Tianjin-Hebei delta, and the Yangtze River delta together account for more than 80% of the industrial output of the Chinese market. Changzhou in the Yangtze river delta was selected as a standard due to the good availability of its data and its representation of the region [30]. Deviations from these values are provided with a penalty (e.g. 0.9) or a commendation term (e.g. 1.1) depending on the direction of the effect (see Fig. 2 (b)). In addition, three expert interviews were conducted to quantify the influence of location factors on twelve selected technologies (see Fig. 2 (c)). These two tables can be used to define the location factors for the region of the company and subsequently calculate a reduction term for the needed implementation effort. For the standard location, for instance, the needed effort to implement a Pick by Light system is reduced by 27%. Consequently, the Catalog can also be used to consider resource-saving aspects when selecting sites. Another online survey with 79 participating companies from the three previously defined regions, determines the significance of different KPIs per region (see Fig. 2 (a)). To calculate a single objective value pairwise comparison and standardization can be used for the most important KPIs of a region [31].

To quantify the two types of interdependencies (prerequisites and TS; see Formula 2) and the location independent implementation efforts three expert interviews were conducted. The influence of the technologies (TI; see Formula 2) was measured by experiments in a learning factory in Suzhou. In the experiments twenty-four samples were selected for each technology, respectively one-half samples without and the other half were processed with SmAu technology. The changes of performance in form of process data were compared in these two situations. Accordingly, the influence of the technologies was presented.

3.3. Multimethod modeling of SmAu

After the relevant data has been quantified in the previous section, a simulation model can be developed. It is helpful to divide the model into two parts. On the one hand, the

implementation of the SmAu technology and its interdependencies can be modeled via system dynamics, while on the other hand, the production line itself and the resulting KPIs can be modeled via discrete event simulation (see Fig. 1). This enables more flexibility regarding changes and reusability for other purposes. Though, a clearly defined interface between the two models is necessary. Instead of modeling the SmAu technologies as own objects in the DES, their impact will be considered. This may decrease the accuracy of the results, but at the same time drastically decreases the required time to build the model. Because the production line itself is modeled, the accuracy is still expected to be higher than solely using SD as depicted in section 2. It allows the modeler to use the change in the process data as a connection between the models (see Fig. 1). Process data describe the elements of a value stream map, defining the KPIs of an element such as cycle time or defect rate [32].

The SD model depicts mainly three factors. First the implementation progress of a single technology. The performance of a technology usually does not correlate linearly with the implementation progress. Due to resistance among employees regarding the change [33], the need for training and a low perception of the technology's usefulness [34], it only rises slowly at the beginning of an implementation. With advancing progress these barriers decrease, causing a faster increase in performance until it slowly runs out at the end as the final small changes are implemented. Therefore, a sigmoid function for the implementation degree $f(x)$ is assumed (see Formula 1) based on the *totalEffort* needed to implement the technology and the days x already invested in the implementation. The implementation degree lies on an interval between 0 and 1.

$$f(x) = \frac{1}{1 + e^{-12 * (\frac{x}{totalEffort} - 0.5)}} \quad (1)$$

The next factor is related to the prerequisites of SmAu technology. These should be able to occur in chains. This means a SmAu technology can only be used if all prerequisites are implemented as well as their prerequisites. As a third factor, it must be modeled how the support between technologies develops. In contrast to the prerequisites, chains are not being considered here as indirect efficiency or effectiveness effects are rather scarce in practice. This also intends to prevent excessive complexity. In addition, a maximum limit of absolute support should be modeled as most technologies only have limited improvement potential. A digital shop floor management, for example, cannot improve infinitely by implementing more technologies that provide data.

A crucial challenge in modeling the DES model is to balance the contradictory interests between accuracy and runtime. The more detailed the production line is modeled, the longer the simulation run takes. This is crucial for the following sequence selection. The focus should be on the elements that are determined by or influence the initially selected process data.

3.4. Sequence reduction and selection

After gathering the input data and setting up the simulation model, the simulation of the SmAu technologies can be applied to select the best implementation sequence. In this case, the total number of possible sequences equals the factorial of the number of technologies. Therefore, a substantial reduction is necessary before analyzing potential sequences in detail.

As a first step, the number of technologies is reduced, if possible, as this significantly decreases the total number of possible sequences. The technologies are clustered if prerequisites form a directed loop, meaning that an effect will only occur after all the affected technologies have been implemented, or if two technologies are otherwise bound closely together. The latter can refer, for example, to the required resources. Furthermore, it is possible that, from a strategic point of view, certain company-defined rules exist that technologies have to be implemented first or last.

After clusters and or rules have been formed all sequences can be eliminated in which a prerequisite is implemented after the dependent technology. This reduction is substantial as each prerequisite reduces the number of potential sequences by around half or two thirds, depending on whether they are connected in a chain.

The next step intends to calculate a rough estimation of the output for each sequence. For this purpose, every process data is slightly changed after another and the effect of this action on the objective KPIs is measured via the simulation model. The result is a rough indication of the influence of the individual process data on the target value PK . This information can be multiplied by the direct TI and indirect impact $TS*TI$ of the technologies to the process data, obtained in chapter 3.2. Indirect impact relates to technologies that mainly improve the direct impact of another technology by supporting it (see Formula 2). This results in a matrix that shows the estimated influence of each technology on the objective value TK .

$$((TS * TI) + TI) * PK = TK \quad (2)$$

To rank each sequence, it is assumed that the earlier a technology (i) with a high impact is implemented, the higher the final objective value. Therefore, the counter value (n equals the number of technologies) of the rank is multiplied by the impact TK and the sum of all technologies in one sequence calculated (see Formula 3).

$$\sum_{i=1}^n (n - rank_i) * TK_{i,1} = estimatedOutput \quad (3)$$

The sequences with the highest expected outcome are selected and further analyzed via simulation. Since the result of each simulation run partly depends on probability distributions in the production line that are not necessarily connected to the implemented technology, several replicates of the same sequence are simulated. As a rule of thumb, at least five replications should be run [35].

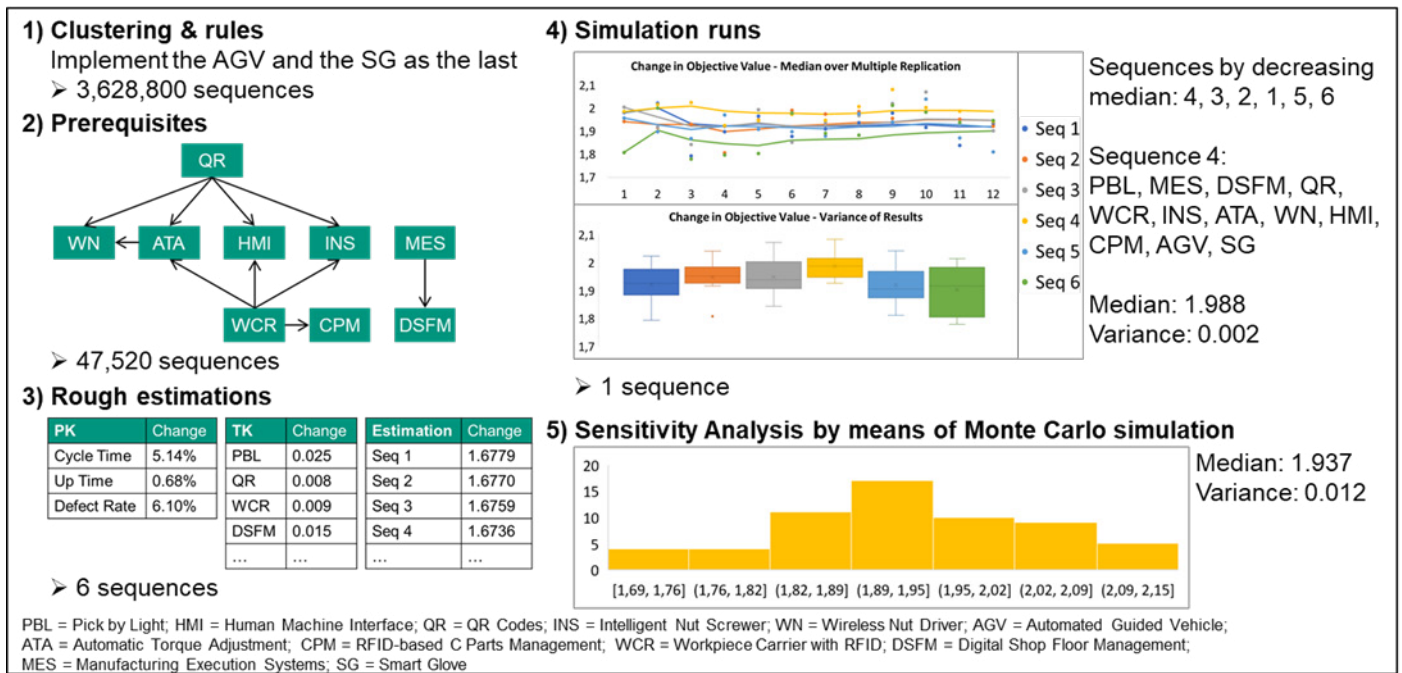


Fig. 3 Results from the use case

Depending on the statistical significance of the results, further replicants can be performed for individual sequences. The best sequence can be selected using standard statistical measures like the mean value or the variance.

Because many interdependencies in section 3.2 are quantified by conducting expert interviews, a sensitivity analysis of the location criteria, the technology support and the technology impact is necessary to confirm the goodness of the selected sequence. Thereby those values are varied in a Monte Carlo simulation. As the quantity is supposed to be further analyzed, only those values are varied which the expert determined to be larger than zero.

The described approach results in a single sequence whose sensitivity has been tested and which gives guidance for a detailed implementation planning. Here, other factors like the availability of resources and cost analysis are considered in more detail.

4. Case study

A case study at a German-Chinese small-sized company, located in Suzhou, is carried out. A key feature of the company is a learning factory which consists of a semi-autonomous production line. As it fulfills most of the properties of the defined company profile and is located in the reference region, the Yangtze-River Delta, it is perfectly suitable to validate the approach. The goal is to find an implementation sequence for twelve selected technologies. As companies in the Yangtze-River Delta mainly focus on quality costs, OEE and lead time, the change of these KPIs is measured and weighted to calculate an objective value. Because the region is especially preferable to manufacturing companies due to a high education level, the total implementation effort needed for all technologies is decreased by the location from 2,030 days to 1,626 days.

The company produces a single type of valve and has four assembly stations and an extra station for a quality check which are connected in series. Each station has a buffer with a maximum of five pieces. Regarding the selected KPIs three process data items are chosen, cycle time, uptime and defect rate. Based on Aull [16], a maximum support level that a single technology can receive from other SmAu technologies is set to 25% for all technologies except the digital shop floor management and the MES. As these two are especially dependent on data from other technologies, it is assumed that their efficiency can increase by a maximum of 50% through the support of other technologies. Due to low prioritization of intralogistics, the AGV, and due to unsatisfactory maturity, the smart gloves are implemented as the last two technologies. This reduces the number of potential sequences from almost 500 million to around 3.5 million. Especially QR codes and workpiece carriers with an RFID chip are important prerequisites to other technologies like the automatic torque adjustment. Considering these and the other prerequisites (see Fig. 3) reduces the number of potential sequences further to 47,520 as those technologies have to be implemented before the dependent technologies. For the rough estimation, five simulation runs are conducted per process data item in which the value is decreased by 10%. Especially, the defect rate has proven to be influential on the final KPI (see Fig. 3). Because of this, all six sequences with the highest expected result implement pick by light as the first or second technology as it is expected to have the greatest impact on the defect rate. Based on twelve replicates for each of the six sequences, sequence four improves the objective value the most. It is expected to halve the quality costs and the lead time and increase the OEE by 60%. Finally, the Monte Carlo simulation shows that the sequence is stable as the variance is only 0.012 after 60 variants.

5. Conclusion

Concluding, this paper shows an approach to derive a regionalized implementation strategy for SmAu technologies. By considering the interdependencies of the technologies as well as the dependencies with location factors, company-specific attributes, and KPIs, a more comprehensive solution is achieved. A multimethod simulation considers the company's production line in order to give individualization apart of the location. This enables an experiment setting with which a reduction of the potential sequences can be done in four steps. By this, companies gain a deeper understanding of the different implementation strategies and how the technologies influence their production.

As the quality of the results depends on the quality of the data, it is recommended for future research to improve the quantification of the dependencies. Compared to similar approaches reviewed in chapter two the quality can be considered to be significantly higher as the production line is modeled and not just assumed. Because the timeframe of the implementation covers multiple years, it should be considered how the data changes over time. Especially the location factors are likely to alter during the execution of the model.

Acknowledgements

This research and development project is funded by the German Federal Ministry of Education and Research (BMBF) within the Industry 4.0 Factory Automation Platform - I4TP (funding number 50694) and managed by the Project Management Agency Karlsruhe (PTKA). The author is responsible for the contents of this publication.

References

- [1] Kennedy S. Made in China 2025. Center for Strategic & International Studies. <https://www.csis.org/analysis/made-china-2025> [06/22/2018]; 2015.
- [2] The State Council of China. Made in China 2025. White paper; 2015.
- [3] Deloitte LLP. 2016 Global Manufacturing Competitiveness Index; 2016.
- [4] Yang S, Boev N, Haefner B, Lanza G. Method for Developing an Implementation Strategy of Cyber-Physical Production Systems for Small and Medium-sized Enterprises in China. *Procedia CIRP* 76; 2018. p. 48-52.
- [5] Greinacher S. Simulationsgestützte Mehrzieloptimierung schlanker und ressourceneffizienter Produktionssysteme. Shaker Verlag; 2017.
- [6] BMWi. Impulse für Wachstum, Beschäftigung und Innovation; 2015.
- [7] Zhou K, Liu T, Zhou L. Industry 4.0: Towards future industrial opportunities and challenges. In *Fuzzy Systems and Knowledge Discovery*. 12th International Conference; 2015. p. 2147-2152.
- [8] Bauernhansl T. Die vierte industrielle Revolution: Der Weg in ein wertschaffendes Produktionsparadigma. In *Handbuch Industrie 4.0 Bd. 4*. Berlin, Heidelberg: Springer; 2017. p. 1-31.
- [9] Deuse J, Weisner K, Hengstebeck A, Busch F. Gestaltung von Produktionssystemen im Kontext von Industrie 4.0. In: Bothof A, Hartmann EA. *Zukunft der Arbeit in Industrie 4.0*. Berlin, Heidelberg: Springer; 2015. p. 99-109.
- [10] Ma TB, Xu JH. Study on the Implementation Strategy of Liaoning Manufacturing Collaborative Innovation System Based on "Made in China 2025". In *Proceedings of the 23rd International Conference on Industrial Engineering and Engineering Management*. Paris: Atlantis Press; 2016. p. 173-176.
- [11] Wang S, Wan J, Li D, Zhang C. Implementing smart factory of Industrie 4.0: an outlook. *International Journal of Distributed Sensor Networks* 12(1); 2016.
- [13] Liebrecht C, Schwind J, Grahm M, Lanza G. A three-step transformation process for the implementation of Manufacturing System 4.0 in medium-sized enterprises. 7. WGP-Jahreskong. Aachen; 2017. p. 251-260.
- [14] Sarvari PA, Ustundag A, Cevikcan E, Kaya I, Cebi S. Technology Roadmap for Industry 4.0. In: Ustundag A, Cevikcan E. *Industry 4.0: Managing The Digital Transformation*. Cham: Springer International Publishing; 2018. p. 95-103.
- [15] Jondral AG. Simulationsgestützte Optimierung und Wirtschaftlichkeitsbewertung des Lean-Methodeneinsatzes. Shaker; 2013.
- [16] Aull F. Modell zur Ableitung effizienter Implementierungsstrategien für Lean-Production-Methoden. Herbert Utz Verlag; 2013.
- [17] Tako AA, Robinson S. The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision support systems* 52(4); 2012. p. 802-815.
- [18] Serman JD. System dynamics modeling: tools for learning in a complex world. In *California management review* 43(4); 2001. p. 8-25.
- [19] Hedtstück U. Simulationstechniken für diskrete Prozesse. In: Hedtstück U. *Simulation diskreter Prozesse: Methoden und Anwendungen*. Berlin, Heidelberg: Springer; 2013. p. 21-37.
- [20] Balaban M, Hester P, Diallo S. Towards a theory of multi-method M&S approach: part I. In *Proceedings of the 2014 Winter Simulation Conference*. IEEE Press. p. 1652-1663.
- [21] Lee YH, Cho MK, Kim YB. A discrete-continuous combined modeling approach for supply chain simulation. *Simulation* 78(5); 2002. p. 321-329.
- [22] Law AM. *Simulation modeling and analysis*. New York: McGraw-Hill Education; 2015.
- [23] März L, Krug W, Rose O, Weigert G. *Simulation und Optimierung in Produktion und Logistik: Praxisorientierter Leitfaden mit Fallbeispielen*. Springer-Verlag; 2010.
- [24] Swisher JR, Jacobson SH, Yücesan E. Discrete-event simulation optimization using ranking, selection, and multiple comparison procedures: A survey. *ACM Transactions on Modeling and Computer Simulation* 13(2); 2003. p. 134-154.
- [25] Dombrowski U, Ebentreich D, Krenkel P. Impact analyses of lean production systems. *Procedia CIRP* 57; 2016. p. 607-612.
- [26] Peter K. *Bewertung und Optimierung der Effektivität von Lean-Methoden in der Kleinserienproduktion*. Shaker; 2009.
- [27] Liebrecht C, Schaumann S, Zeranski D, Antoszkiewicz A, Lanza G. Analysis of Interactions and Support of Decision Making for the Implementation of Manufacturing Systems 4.0 Methods. *Procedia CIRP* 73; 2018. p. 161-166.
- [28] Abele E, Meyer T, Näher U, Strube G, Sykes R. *Global production: a handbook for strategy and implementation*. Springer Science & Business Media; 2008.
- [29] Schuh G, Brosze T, Brandenburg U, Cuber S, Schenk M, Quick J. *Grundlagen der Produktionsplanung und -steuerung*. In *Produktionsplanung und -steuerung 1*. Berlin, Heidelberg: Springer; 2012.
- [30] China Academy of Fiscal Sciences. *Reducing Business Costs: Survey and Analysis by CAFS*. Beijing: 1st edn. China Financial & Economical Publishing House; 2017.
- [31] Wenzel S, Weiß M, Collisi-Böhmer S, Pitsch H, Rose O. Qualitätskriterien für die Simulation in Produktion und Logistik: Planung und Durchführung von Simulationsstudien. Springer; 2007.
- [32] Lacerda AP, Xambre AR, Alvelos HM. Applying Value Stream Mapping to eliminate waste: a case study of an original equipment manufacturer for the automotive industry. *International Journal of Production Research* 54(6); 2016. p. 1708-1720.
- [33] Friedman E. *Wearable Technology by Industry Series*. *EnterpriseWear Blog* vol. 18; 2015.
- [34] Borhani AS. Individual and Organizational Factors Influencing Technology Adoption for Construction Safety; 2016.
- [35] Law AM, McComas MG. Pitfalls in the simulation of manufacturing systems. In *Proceedings of the 18th conference on Winter simulation*; 1986. p. 539-542.