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# Cyber-Physical Production Systems Combined with Logistic Models – A Learning Factory Concept for an Improved Production Planning and Control

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## Abstract

Nowadays, production enterprises are faced with an array of challenges including increasing pressure regarding costs, demands for individualized products as well as the growing significance of logistic performance and costs, to name just a few. These in turn give rise to special requirements that the production planning, control and monitoring, among others, need to meet with suitable methods and techniques. Within this context, developments such as Industry 4.0 and cyber-physical production systems on the technology side, and approaches such as innovative learning factories for training employees hold great potential.

This paper clarifies the advantages of cyber-physical systems in view of production planning, controlling and monitoring. Based on that, using the concept of IFA's Learning Factory, it describes how these can be specifically utilized in applying logistic models to improve order processing.

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## 1. Introduction

A large part of the production industry has been confronted with continually increasing competition for many years [1]. While the pressure to reduce costs steadily grows, their logistic performance is simultaneously gaining importance. This influential development has meant that it is no longer sufficient to exclusively focus on product features in order to maintain market success [2], [3]. Whereas, products barely differ in prices and quality and thus offer little room for an enterprise to distinguish themselves, realizing a strong logistic performance creates the possibility for a company to optimally position themselves against competing producers [4]. In addition to realizing a strong logistic performance, characterized by quick delivery times and high delivery reliability, today's production logistics also focus on diminishing costs by maintaining a minimum of stock and highly utilizing capacities [5]. Demands on the logistic performance and costs will continue to grow in the future. It will thus become all the more important not only for the

production planning and control to be more efficient and more closely oriented on logistics, but also for the production to be monitored in terms of reaching targets. This is associated with two main challenges for production enterprises.

First, it is more and more necessary to have suitable approaches, methods and tools for analyzing production systems and supply chains in view of targets and for optimally organizing operational processes. In this context, a number of logistic models have already been developed (in particular at IFA – the Institute of Production Systems and Logistics) for solving various problems in organizing operations involved in processing orders and have been successfully implemented in the practice. One of the key challenges in practically applying these however, is supplying the required data. All too often the quality and quantity of the compiled data is insufficient for these purposes. The development of cyber-physical systems (CPS) and cyber-physical production systems (CPPS) as well as the application of Big Data Analyses hold great potential in this regard though.

Second, employees' competences, expertise and know-how

are taking on significance. Generally, the increasingly dynamic demands of markets, shorter product life cycles as well as the challenges placed on employees as a result of technical innovations and more complex production systems require the workforce to continually improve their practice-related qualifications and training [6], [7]. In view of the above described problematic, internal competences are critical because the logistic performance and cost objectives are influenced by numerous interactive mechanisms. Decisions that are made within the frame of the Production Planning and Control (PPC) and targeted at these objectives have to be consciously made on the basis of technical considerations, since wrong decisions can quickly lead to contrary outcomes. Current trends such as employees changing jobs more frequently or the impact of knowledge aging require new learning approaches [8], more than ever. In recent years, the concept of learning factories has proven to be particularly useful here.

Against this background, the “IFA Learning Factory” was created as a further development of “IFA Production Trainers” at the Leibniz Universität Hannover. The IFA Learning Factory not only facilitates improved production planning and control but also allows production to be monitored using logistic models which utilize recorded operating data. This paper describes the concept of the IFA Learning Factory in relation to PPC and monitoring while at the same time demonstrating how enterprises can both orient their PPC on requirements through the development of cyber-physical production systems and orient their production monitoring on targets by implementing logistic models.

## 2. Theoretical Fundamentals

### 2.1. Basics of Learning Factories

As discussed in the introduction, enterprises are confronted with challenges that require the education and continued education of students and employees at industrial enterprises to have a strong practical orientation. Together with the need for action-oriented learning, the concept of a learning factory has gained significance. A plethora of definitions can be found in publications for the term “learning factory” (see e.g. [9], [10]). Generally speaking though, it can be understood as a practice-oriented learning environment for students and employees from the industry [6], which encompasses a more or less complex production environment. Moreover, it allows various possibilities to configure and intervene in the operational processes (i.e., in the manufacturing, assembly and logistic processes), which in contrast to a real production, can however, be conducted without financial risk [11], [12]. The goal of the learning factory is to offer participants a learning environment which allows a balanced relationship in conveying specialized theoretical and analytical knowledge as well as hands-on experience. Moreover, the aim is to facilitate learning experiences that have a strong connection with practical problems [13], [14]. Against the background of the increasing demands on employees’ knowledge and know-how in an enterprise, as well as the possibilities for action-oriented learning, the simple mediation of methods with the

opportunity to test them without risk and the related improved learning success has brought the concept of learning factories considerable consideration in the last years. In the interim, many universities and enterprises have developed their own learning factories and implement them in further educating students and employees. Learning factories are also gaining attention on the research side. Wagner et al. [15] conducted a survey on the use of learning factories in research, teaching and the industry and developed a schema for classifying learning factories. Tisch et al. [13] developed a learning factory curriculum guide, which offers a systematic approach to establishing action-oriented and competency-based learning factories. In turn, Cachay et al. [11] examined how the learning factory concept impacted the application-performance of students and came to the conclusion that implementing learning factories can clearly have a positive influence on students’ performances in comparison to traditional teaching.

### 2.2. Production Planning and Control

Orienting the production planning and control on targets as well as efficiently monitoring the production is indispensable for successfully and economically operating a production system. In this context, production planning and control (PPC) is responsible for organizing all of the planning and control operations in an enterprise’s flow of goods [16], [17]. The key objects of consideration include planning and controlling all operational production processes related to schedules, capacities and quantities. Whereas the production planning concentrates on configuring the content and individual processes of the manufacturing and assembly, production control organizes the sequence of all the activities within the order processing and is directed at implementing planned targets and attaining the logistic objectives [18]. Since PPC is largely responsible for attaining economic and logistic objectives, it plays an extremely important role in the operational context and thus also in teaching and in many learning factory concepts. However, especially in view of the increasing complexity of product structures and diversity of variants, quantitative statements about the impact of PPC measures or methods on the logistic objectives (i.e. WIP, throughput time, lateness and utilization) are hard to make without appropriate models.

In addition to measuring the attainment of logistic objectives, production monitoring is responsible for comparing the actual and planned data, identifying possible causes of deviations that arise, deriving measures to counter deviations as well as uncovering potential for streamlining. Whereas planning data is generated by the PPC system, feedback data from the production or the time and cost variables determined from the feedback data represent the actual data [5] [17]. When monitoring the production in terms of logistics, the primary focus should be on the logistic objectives: WIP, utilization, throughput time and schedule reliability. The key figures determined in monitoring the production represent vital information for decisions made by PPC, since it is through them that the impact of measures within the order processing can be measured. The key figures

are also important performance indicators of a production, which is why they are frequently used to measure the logistic performance of a production system.

2.3. Logistic Models

In order to efficiently monitor the production and control-decisions based on it in view of the operational goals, complete and consistent data is first required. In order to attain valid planning results and to make targeted control decisions it is also necessary to know the interactions that exist between the production logistics in a supply chain. Especially in consideration of the continually increasing significance of the logistic objectives, the impact of material planning and structural measures on the logistic objectives have to always be taken into account. Only then is it possible to sustainably organize operational processes along the order processing. The logistic models developed at the Institute of Production Systems and Logistics (IFA) are particularly helpful for this as they allow an application oriented description and analysis of the interactions between the production logistics.

With the aim of realizing a consistent model based description of an internal supply chain i.e., from procurement to production and up to distribution, an array of descriptive, impact and decision-making models have been developed in the last decade at IFA. These models are characterized by the detail with which they describe existing interactions between logistic objectives. Due to the possibility to analyze complex operational sequences with the aid of these models and to orient these on different conditions, they are ideal for configuration and steering related tasks [19]. As a result of their ability to qualitatively clarify and quantitatively describe existing interactions the models have already been integrated in numerous approaches for monitoring, planning and controlling productions. The variables used as input data or for calculations in the models include different operating data e.g., input and output dates for orders on a system or in a store, setup times, piece unit times, capacities etc. By orienting the models of the four reference processes (storage, transportation, manufacturing and assembly) it is also possible

to describe and analyze a full array of differently structured supply chains. An overview of the basic models developed at the Institute of Production Systems and Logistics is provided in Fig.1.

2.4. Cyber-physical Production Systems

In recent years, the term “cyber-physical system” (CPS) has often been used as a synonym both in research and in practice. Already a few years ago, these systems were described by Lee as follows: “Cyber-physical systems (CPS) are integrations of computation and physical processes. Embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa” [20]. Cyber-physical systems include embedded systems such as equipment, buildings, transportation means, and medical devices, but also logistic, coordination and management processes as well as internet services [21]. With the aid of sensors cyber-physical systems are able to directly collect, process and evaluate data, while actuators allow them to react to changes and digital communication facilities allow them to interact with other cyber-physical systems [22], [23]. There is thus a direct connection between the physical and digital world [23]. Within these systems data is independently and mutually exchanged in real time, thus allowing a mutual control system. Cyber-physical systems can be implemented across an extremely broad spectrum e.g., Smart Mobility, Smart Health, Smart Grid or Smart Factory [21]. In relation to smart factories, a cyber-physical production system (CPPS) can be created when multiple cyber-physical systems are connected and interact with one another [24], [25].

With data volume steadily increasing and the variety of data continually growing, the term “big data” is often used. However, not only are the origins of this term unclear, there are also a variety of descriptions. The McKinsey Global Institute defines big data as “large pools of data that can be captured, communicated, aggregated, stored, and analyzed” [26]. Accordingly, the concept of “big data analytics” refers to newly developed methods for analyzing large and complex data volumes [27].

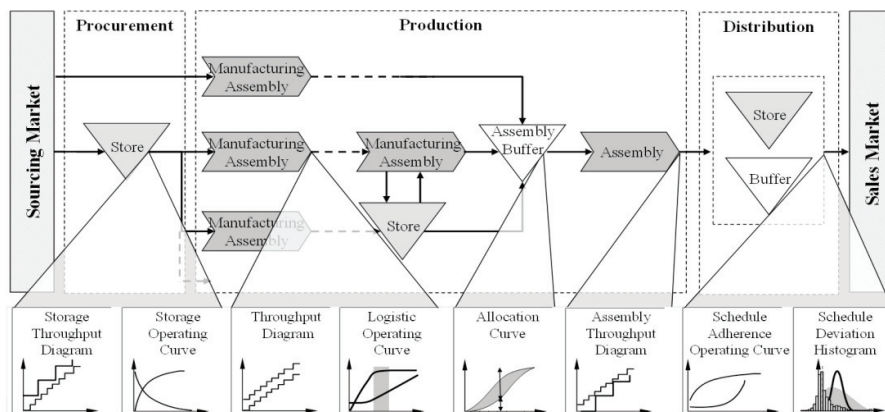


Fig. 1. Overview: Logistic models

### 3. Challenges in Planning, Controlling and Monitoring Productions

In the preceding section we described how goal-oriented PPC significantly impacts logistical targets and how a logistics-oriented production monitoring is in turn built on a sound data base. Productions can only be effectively planned, control and monitored when the relevant employees possess the necessary knowledge about methods and logistic interactions. They need to be able to apply methods as well as conduct analyses and then to make decisions based on the results. In turn, the employees involved in implementing the decisions, also have to be able to understand the decisions, in order to be able to implement them accordingly. In addition to technological or IT based solutions for collecting and supplying data, there are thus also extensive demands on the knowledge and competences of an enterprise's employees.

These requirements nevertheless, pose challenges for many of today's production systems. On the one hand, an inappropriate number of feedback points that are wrongly positioned and/or operating data which has not been properly acquired or maintained leads to an incomplete and often inconsistent database [28]. According to a study conducted by Schuh et al. [29], production data feedback is currently submitted in written and not digital form in 59% of small and medium sized enterprises and 30% of large enterprises. Under such circumstances it is almost impossible to efficiently monitor a production with valid results. On the other hand, many enterprises lack the required expertise and knowledge about both production logistic methods and the interactions occurring within logistics.

In view of data acquisition the previously mentioned innovations and developments in the area of cyber-physical systems offer significant potential since they are capable of independently and economically compiling data in real-time and in the right quality/quantity for monitoring the production. Through the sensor technology within a cyber-physical production system real time data is continually acquired during the order processing or order throughput. With the support of big data analyses the data required for monitoring the production are extracted from the total data volume and processed as specified. Using logistic models, the

processed data is in turn analyzed and evaluated within the frame of monitoring the production. The analyses results and logistic figures then allow conclusions to be drawn for the production planning and control in order to improve the performance of the production system, (see Fig. 2).

By combining cyber-physical systems and big data analyses with the previously described logistic models it is possible to develop production systems that allow operational production processes to be optimally organized in terms of costs and logistics. Based on the IFA Learning Factory and with an eye to monitoring a production or the related PPC, we will now show how cyber-physical production systems can generally function. At the same time, the concept of the IFA Learning Factory conveys the required expert knowledge to participants and therefore provides an important contribution to designing more efficient, logistics-oriented production systems.

### 4. Concept of the IFA Learning Factory

The IFA Learning Factory is a project of the Institute of Production Systems and Logistics (IFA) which aims to provide both students and professionals from the industry with a realistic and at the same time innovative opportunity to study theoretical and practical issues in designing and controlling production systems. The focus is placed in particular on the organization of manufacturing and assembly processes in order to realize an efficient and customer-oriented order processing. The integrative training at the IFA Learning Factory covers topics such as Lean Production, PPC, production monitoring as well as modules on workplace ergonomics and factory planning.

In view of the above described challenges, one of the key requirements in developing the IFA Learning Factory was realizing a real-world production environment that comprises the characteristics of a cyber-physical production system in relation to the data availability. Based on a comparably simple IT infrastructure with an integrated PPC system, the aim was to allow logistic models to be implemented using captured near-real time data to improve the PPC and production monitoring. Additionally, it was designed to include the possibility to flexibly configure all of the control-relevant

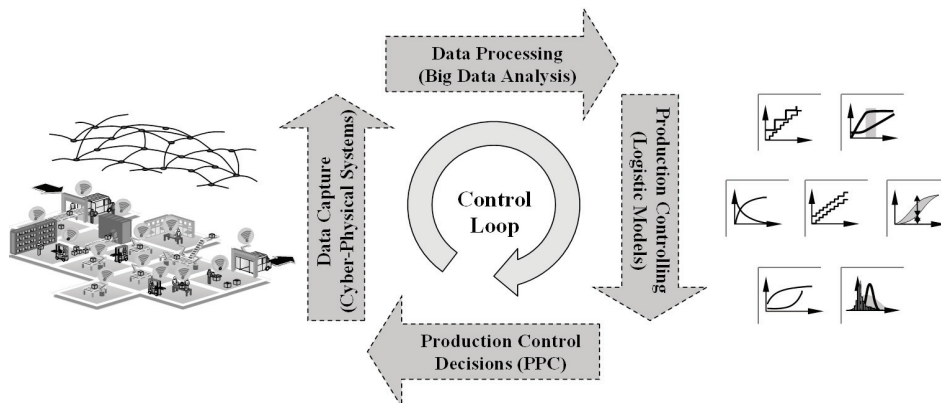


Fig. 2. Cyber-physical production systems with logistic models



methods and parameters in the production environment, so that for example, different order release methods could be implemented and compared to one another. This would enable model-based analyses to be conducted using the acquired operation data within the context of monitoring the production’s logistics. Subsequently, the PPC could then be flexibly configured and the control decisions that arise from these analyses (e.g., changes in lot sizes, alternative order releases or sequencing methods) can be directly implemented.

This concept was realized in developing a production for aluminium helicopter models consisting of two divisions for manufacturing and assembling components. Real manufacturing methods such as the milling of rotor blades are employed. In order to fully exploit the advantages of action-oriented learning all work operations are completed by the training participants. Whereas the manufacturing of the helicopter components with its crossing material flows, fluctuating work content and shifting processing times is characteristic of a traditional manufacturing workshop, the assembly of the components is completed on a flexibly configured assembly line. This structure makes it possible to address various problems from the industrial practice as well as to more closely consider the different conditions found in participating enterprises and to focus on relevant issues.

In order to implement the required features (in relation to the organization of operational processes) of a cyber-physical production system in the IFA Learning Factory and to enable the acquisition and processing of approximately real-time production data, all of the learning factory’s workstations were first equipped with suitable IT infrastructure. Furthermore, a PPC system that was easy for training participants to use was developed based on Microsoft® Access. This system networks all of the workstations together and allows them to communicate order data with one another. All of the data and information required for production, such as work plans, capacity data and data about resources are also saved in this system. In the course of the simulation and practice rounds, the PPC system generates manufacturing jobs from the incoming customer orders. Using backwards

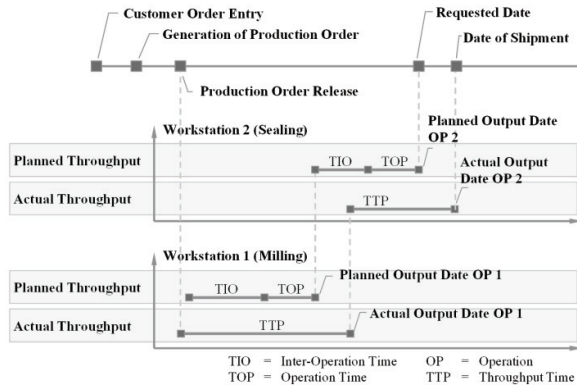


Fig. 3. Determining due dates

scheduling and depending on the work plan’s data, inter-operation times and customer’s desired due dates, it determines the corresponding planned due dates (see Fig. 3). Further the system transmits the required manufacturing job data to the workstations and at the same time saves the feedback data supplied by the station. This data is then directly imported into the logistic models (programmed in Microsoft® Excel) and can be evaluated. The returned actual data (e.g., order completion dates from workstations) can be compiled either via sensors or manual feedback. The thus acquired data can be analyzed with the aid of the logistic models in order to measure the logistic performance of the production system using key figures, used to investigate causes of possible deviations from set targets and to derive appropriate control decisions. Due to the specifically defined feedback and the resulting comparatively low data volume (as compared to continual data acquisition in large productions) special big data analyses (as depicted in Fig. 2) are not required for extracting relevant data in the IFA Learning Factory.

Among the logistic models implemented in the IFA Learning Factory is the throughput diagram [30]. The

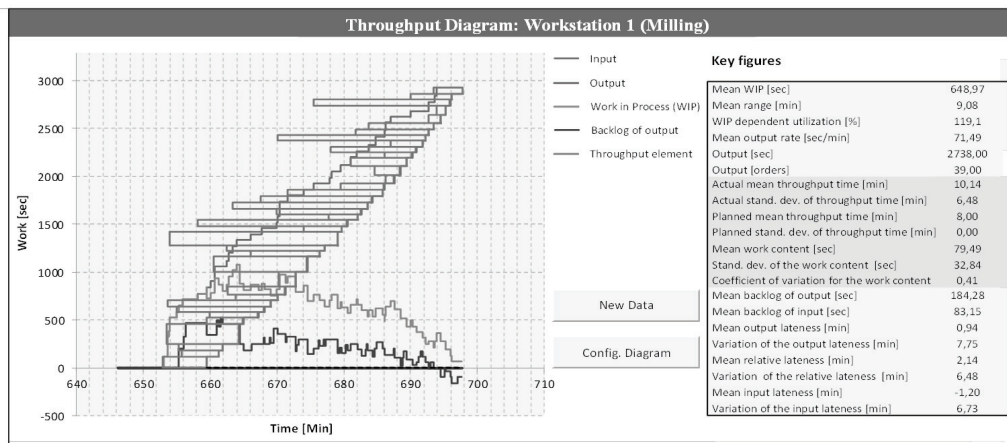


Fig. 4. Exemplary throughput diagram and key figures (screenshot)

throughput diagram visualizes the behavior of every workstation by plotting the order inputs and outputs during the practice rounds and is supplemented with the calculated key logistic figures.

As an example, Fig. 4 depicts a throughput diagram for a workstation which was generated during a training at the IFA Learning Factory. On the left side of the figure, the workstation's behavior is depicted progressively over time through the representation of the orders' inputs and outputs along with the WIP and backlog trends. On the right side, the key logistic figures calculated from the operating data are listed. Both sets of information can be used to verify objectives and to draw conclusions about the PPC.

## 5. Conclusion

Based on the continually increasing demand for greater logistic performance and lower logistic costs, this paper describes the challenges faced by production enterprises when planning and controlling their order processing. Within this context, it was shown that in terms of attaining logistic objectives and increasing an enterprise's competitiveness, there is generally tremendous potential both in compiling, supplying and analyzing operational data as well as in the area of employee competences and know-how. Following that a brief introduction to the concept of learning factories as well as production logistics and technologies led to a description of how cyber-physical systems in combination with logistic models can improve planning, controlling and monitoring a production. At the same time, with the IFA Learning Factory, this paper has introduced a learning factory concept in which the advantages of cyber-physical production systems can be specifically used for planning, controlling and monitoring production systems and simultaneously implemented for further qualifying and educating students and employees from the industry.

## References

- [1] Wiendahl H.-P., Reichardt J., Nyhuis P., Handbuch Fabrikplanung, Konzept, Gestaltung und Umsetzung wandlungsfähiger Produktionsstätten, Carl Hanser Verlag, München, Wien, 2009.
- [2] Wildemann H., Entwicklungstrends in der Automobil- und Zulieferindustrie. Empirische Studie, TCW Transfer-Centrum, München, 2009.
- [3] Wiendahl H.-P., Erfolgsfaktor Logistikqualität. Vorgehen, Methoden und Werkzeuge zur Verbesserung der Logistikleistung, 2.Auflage, Springer Verlag, Berlin, Heidelberg, New York, 2002.
- [4] Spath D., Demuß L., Entwicklung hybrider Produkte – Gestaltung materieller und immaterieller Leistungsbündel, in: H.-J. Bullinger, A.-W. Schweer, Service Engineering Entwicklung und Gestaltung innovativer Dienstleistungen, Springer Verlag, Berlin, Heidelberg, New York, 2006, p.463-502.
- [5] Nyhuis P., Wiendahl H.-P., Fundamentals of Production Logistics, Theory, Tools and Applications, Springer Verlag, Berlin, Heidelberg, 2009.
- [6] Kreimeier D., Morlock F., Prinz C., Krückhans B., Bakir D. C., Meier H., Holistic learning factories – A concept to train lean management, resource efficiency as well as management and organization improvement skills, Procedia CIRP 2014, Vol. 17, pp.184-188.
- [7] Matt D. T., Rauch E., Dallasega P., Mini-factory – a learning factory concept for students and small and medium sized enterprises, Procedia CIRP 2014, Vol. 17, pp. 178-183.
- [8] Abele E., Reinhart G., Zukunft der Produktion: Herausforderungen, Forschungsfelder, Chancen. Carl Hanser Verlag, München.
- [9] Roth A. V., Marucheck A. S., Kemp A., Trimble D., The Knowledge Factory for accelerated learning practices, Planning Review 1994, Vol. 22 Iss: 3, pp. 26-46.
- [10] Barton H., Delbridge R., Development in the learning factory: training human capital, Journal of European Industrial Training 2001, Vol. 25 Iss: 9, pp.465-472.
- [11] Cachay J., Wennemer J., Abele E., Tenberg R., Study on Action-Oriented Learning with a Learning Factory Approach, Procedia Social and Behavioral Science 2012; Vol. 55, pp.1144-1153.
- [12] Cachay A., Abele E., Developing Competencies for Continuous Improvement Processes on the Shop Floor through Learning Factories– Conceptual Design and Empirical Validation, Procedia CIRP 2012, Vol. 3, pp. 638-643.
- [13] Tisch M., Hertle C., Cachay J., Abele E., Metternich J., Tenberg R., A systematic approach on developing action-oriented, comcoetency-based Learning Factories, Procedia CIRP 2013, Vol. 7, pp. 580-585.
- [14] Lamancusa J. S., Jorgensen J. E., Zayas-Castro J. L., De Ramirez L. M., The Learning Factory-Integrating Design, Manufacturing and Business Realities into Engineering Curricula-a Sixth Year Report Card. In: International Conference on Engineering Education, 2001, pp. 6-10.
- [15] Wagner U., AlGeddawy T., ElMaraghy H., Müller E., The State-of-the-Art and Prospects of Learning Factories, Procedia CIRP 2012, Vol. 3, pp. 109-114.
- [16] Kernler H., PPS der 3. Generation: Grundlagen, Methoden, Anregungen, Hüthig Verlag, Heidelberg, 1995.
- [17] Lödding H., Handbook of Manufacturing Control, Fundamentals, Description, Configuration, Springer Verlag, Heidelberg, New York, Dordrecht, London, 2013.
- [18] Schuh G., Stich V. (Ed.), Produktionsplanung und -steuerung 1, Grundlagen der PPS, Springer Verlag, Berlin, Heidelberg, 2012.
- [19] Nyhuis P., Beiträge zu einer Theorie der Logistik, Springer Verlag, Berlin, Heidelberg, 2008.
- [20] Lee E. A., Cyber Physical Systems: Design Challenges, Technical Report No. UCB/EECS-2008-8, 2008, Electrical Engineering and Computer Sciences, University of California at Berkeley.
- [21] Geisberger E., Broy M., agendaCPS, Integrierte Forschungsagenda Cyber-Physical Systems, acatech Studie, 2012.
- [22] acatech – National Academy of Science and Engineering, Cyber-Physical Systems, Driving force for innovation in mobility, health, energy and production, acatech Position Paper, Springer Verlag, Heidelberg, 2011.
- [23] Broy M., Cyber-Physical Systems, Innovation durch Softwareintensive Eingebettete Systeme, Springer Verlag, Heidelberg, 2010.
- [24] Reinhardt G., et al., Cyber-physische Produktionssysteme: Produktivitäts- und Flexibilitätssteigerung durch die Vernetzung intelligenter Systeme in der Fabrik, wt Werkstatttechnik online, 103 (2), 2013, pp. 84-89.
- [25] Veigt M., Labbe D., Hribernik K. A., Scholz-Reiter B., Entwicklung eines Cyber-Physischen Logistiksystems, Industrie Management (1), 2013, pp. 15-18.
- [26] Manyika J., Chui M., Brown B., Bughin J., Dobbs R., Roxburgh C., Hung Byers A, Big data: The next frontier for innovation, competition, and productivity, McKinsey Global Institute, May, 2011.
- [27] Russom P., Big Data Analytics, TDWI Best Practices Report, Fourth Quarter 2011, Renton , 2011.
- [28] Ostgathe M., System zur produktbasierten Steuerung von Abläufen in der auftragsbezogenen Fertigung und Montage, Herbert Utz Verlag, München, 2012.
- [29] Schuh G. (Ed.), Stich V. (Ed.), Produktion am Standort Deutschland, Aachen, 2013.
- [30] Bechte W., Steuerung der Durchlaufzeit durch belastungsorientierte Auftragsfreigabe bei Werkstattfertigung, VDI-Verlag, Düsseldorf, 1984.