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Procedia CIRP 61 (2017) 335 – 340

www.elsevier.com/locate/procedia

The 24th CIRP Conference on Life Cycle Engineering

The Digital Twin: Realizing the Cyber-Physical Production System for Industry 4.0

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Abstract

Concerning current approaches to planning of manufacturing processes, the acquisition of a sufficient data basis of the relevant process information and subsequent development of feasible layout options requires 74 % of the overall time-consumption. However, the application of fully automated techniques within planning processes is not yet common practice. Deficits are to be observed in the course of the use of a fully automated data acquisition of the underlying process data, a key element of Industry 4.0, as well as the evaluation and quantification and analysis of the gathered data. As the majority of the planning operations are conducted manually, the lack of any theoretical evaluation renders a benchmarking of the results difficult. Current planning processes analyze the manually achieved results with the aid of simulation. Evaluation and quantification of the planning procedure are limited by complexity that defies manual controllability. Research is therefore required with regard to automated data acquisition and selection, as the near real-time evaluation and analysis of a highly complex production systems relies on a real-time generated database. The paper presents practically feasible approaches to a multi-modal data acquisition approach, its requirements and limitations. The further concept of the Digital Twin for a production process enables a coupling of the production system with its digital equivalent as a base for an optimization with a minimized delay between the time of data acquisition and the creation of the Digital Twin. Therefore a digital data acquisition approach is necessary. As a consequence a cyber-physical production system can be generated, that opens up powerful applications. To ensure a maximum concordance of the cyber-physical process with its real-life model a multimodal data acquisition and evaluation has to be conducted. The paper therefore presents a concept for the composition of a database and proposes guidelines for the implementation of the Digital Twin in production systems in small and medium-sized enterprises.

Peer-review under responsibility of the scientific committee of the 24th CIRP Conference on Life Cycle Engineering

Keywords: cyber-physical production systems; multimodal data acquisition; digital twin; production system optimization; Industry 4.0

1. Motivation

In recent years, Industry 4.0 is one of the most prevalent subjects in production engineering. However, methods of industry 4.0 are under-represented within manufacturing operations [1] (p. 7) at this point. This is, on one side, based on non-uniform definitions of Industry 4.0, an issue that current publications counteract against. On the other side, common difficulties as non-existing standards, uncertainties regarding the economical benefits while facing the requirement of sometimes considerable investments [2] (p. 37), as well as the as part of general perception still unsettled matter of data security are apparent [3] (p. 31). Within a 2015 VDMA survey, only 10 % of those surveyed stated to have implemented a comprehensive acquisition of process and machine data. Only a third applied the gained data in a production control feedback [4] (p. 37). Nonetheless, an advantageous use of Industry 4.0 in the course of a value chain cannot be obtained until a vertical implementation of Industry 4.0 in the company itself is ensured [5] (p. 181). Especially the low degree of automation in small and medium-sized enterprises (SME)

Peer-review under responsibility of the scientific committee of the 24th CIRP Conference on Life Cycle Engineering
doi:10.1016/j.procir.2016.11.152

reveals a great requirement for alternative approaches for the realization of a Cyber-Physical Production System (CPPS) [6] (p. 73). Its main aims are to provide and enhance transparency in the production system and allow real-time production control [4] (p. 38), [3] (p. 44), [7] (p. 6). The paper presents a concept for the realization of a Digital Twin of the production system, a core component of Industry 4.0, to assure - providing sufficient data quality - an implementation with minimized investment costs in SME without compromising in matters of the advantages of the Digital Twin and therefore of the CPPS. Herein, an acquisition and transfer of complete set of parameters and data records from production machines is specifically neglected, as this data usually represents the core of competence and expertise of manufacturing companies. A technically feasible solution to data security as part of an inherent approach is introduced. The concept will be implemented in a demonstrator, that proves itself essential for an implementation in SME [3] (p. 35).

2. State of Scientific Knowledge

The following section discusses the state of scientific knowledge regarding the planning of production systems and processes following state of the art methods and simulations.

2.1. Motion Data in Production

The study "Prosense" evinces possibilities to the tracking of products and components in production systems [8] (p. 209), employing the technologies of Beacons and RTLS (real-time locating system). In general, approaches to acquire motion data in production environments are widely limited to RFID (radio-frequency identification) technologies [9] (p. 26). This fact is associated with rather large expenses. Moreover, *Schuh* points out the need for intensified research in the field of real-time localization in production systems as well as the connection to self-optimizing simulation environments [8] (p. 209). Though being desirable, a connection to ERP-systems (Enterprise-Resource-Planning) is regarded as unrealistic for reasons of insufficient standardization [8] (p. 209). Furthermore, ERP-systems mostly rely on manual data inputs that are prone to errors. The extraction of a reliable data source from stock data has no or little prospects of success [8] (p. 209). Motion data is still collected mainly manually [9] (p. 26), even though the potential of automated motion data acquisition for the optimization of production processes is being recognized [10] (p. 35). Concepts exceeding the use of RFID etc. for the localization of objects and personal are subject to ongoing research [11]. Commercial solutions are available and in use [12].

2.2. CPPS

The Cyber-physical Production System is a core component of Industry 4.0 [9] (p. 3). The Digital Shadow and therefore the Digital Twin represents the prerequisite for the development of a CPPS, allowing centralized analysis and control of the production process [9] (p. 31). A useful provision of data, that were acquired for the development of the Digital Twin, requires a cloud-based solution to ensure a near real-time processing [9] (p. 32). Location-independence and remote accessibility of the data provision is an essential criterion for the development of a CPPS [13] (p. 26). To conduct the complex interpretation, a continuous assessment with specialist knowledge is necessary, while a simple transfer of concepts and a non context based data analysis is not promising [14] (p. 98).

2.3. Factory and Production System Planning

Regardless of the degree of automation of single branches and manufacturing companies, a significant increase of the planning expenses has to be noted. [3] (p. 23). Production System Planning can no longer be seen as an only initial planning project. Instead, a continuous production system planning is predominant [15] (p. 14), [16] (p. 18). Manual data acquisition and variation as part of the layout planning contribute up to 74 % of the overall time consumption during the planning process [17] (p. 357), thus conflicts with the requirements of near real-time optimization cycles [18] (p. 19). Traditional methods of process and production planning [17] do not fulfill the demands of near real-time optimization and cannot process the real-time acquired data as a planning basis in a satisfying manner [18] (p. 20). Recently published approaches concerning the cross linking of real and virtual systems examine for example the 3D-imaging of the production system [19] (p. 133). Further investigations focus on special branches or even single production machinery [19] (p. 173,151), that, however, is not in accordance with the aim of branch interdisciplinary solutions for SME [5] (p. 178), and, therefore, is not suitable for an a general assessment of control and continued development of production systems.

2.4. Simulation-based Production Optimization

For years, simulation has been used successfully to solve optimization problems within production and logistic systems [20] (p. VII), [21] (p. VIII). Herein, it has to be noted, that a simulation is not equivalent to an optimization, as the parameter have to be defined and the proposed by the user and solutions have to be evaluated afterwards [17] (p. 377). Consequently, the process of generating varieties is slowed down. A coupling between simulation and optimization is subject to current research. The first approach is formed by the currently prepared VDI 3633, Paper 12. It presents the following coupling approaches:

- simulation to follow optimization
- optimization to follow simulation
- optimization is incorporated into simulation
- simulation is incorporated into optimization

Generally, the foundation of a simulation model is formed by a transfer of the as-is state or planning state [17] (p. 376), to, finally, verify and validate the model using suitable methods [21] (p. 16). The simulation is used for a support of the strategic planning as well as the operating planning [17] (p. 386). This approach uses non-volatile master data and highly volatile time-dependent data are used [16] (p. 248). A difficulty lies in the data quality of the motion data, in particular, that in most of the cases is insufficient for an application in simulative investigations [20] (p. 6). The simulation permits dynamic investigation of production systems, in contrast to the statistical perspective of traditional approaches [16] (p. 239).

2.5. Deficits and Problems

The following difficulties in the course of the realization of the Digital Twin as an essential precondition of a CPPS can be determined:

- manual acquisition of motion data is widely used, though in conflict with necessary real-time availability
- manual acquisition of motion data snapshots limits the potential of simulation
- combined with decentralized data acquisition, a central information system is required [5] (p. 119)
- in-house implementation of Industry 4.0 is frequently insufficient
- slow standardization of data acquisition in productions systems hinders agile and adaptable system implementations [3] (p. 31).
- standardization of data acquisitions has not yet been achieved
- high costs for new IT-environments inhibit the application of vertical Industry 4.0 [3] (p. 31)
- coupling of simulation and optimization is not sufficiently ensured to take full advantage of near real-time models
- data security concerns

3. The Digital Twin for SME

The following section presents a concept for the realization of the Digital Twin in SME. The advantages of this concept regarding data analytics to predict e.g. performance degradation or service needs are widely discussed [22] (p.4) [23] (p. 11). The same advantages apply to the Digital Twin of the production system which significantly contributes to required transparence and to near real-time production control [4] (p. 38).

The innovative character lies in the coupling of well accepted and commercially available or easily realizable components, that are available as isolated solutions at this point. Following the discussion of multi-modal data acquisition with special attention to motion data inside the production system, the coupling with a simulation environment is concerned. System inherent data security through data separation is then explained. Following an explanation for the loss of standardization requirements, agility and scalability of the model are considered. The focus is laid on the production system in the expense of warehousing and logistic processes. However, discoveries within the production system can affect the warehousing process and are in accordance with the recently examined requirements of SME in the context of Industry 4.0 [3] (p. 38, 44).

3.1. Multi-Modal Data Acquisition

The acquisition of motion data combined with knowledge regarding the fields of activities of employees as well as position and use of production machines forms a great potential for the realization of a CPPS. Especially in SME that widely have a low degree of automation, a sole acquisition of information, that consists of time-dependent position data, is not sufficient. A comprehensive image of the production system can only be achieved, if additional information of movements of employees and means of production are considered.

Schuh concludes that because of non-existent standardization of databases in manufacturing companies, a data acquisition from already gathered inventory data will be a long and difficult operation, hence not a realistic approach[8] (p. 209). A comprehensive image of the reality within a production system therefore can only be achieved through a multi-modal data acquisition, similarly to the procedures in modern automobiles (Fig.1) [9] (p. 27). This concept is applied to production systems within this paper.

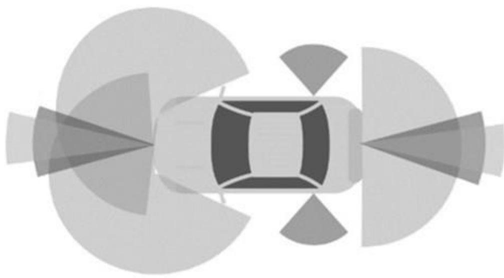


Fig. 1: Example for multi-modal data acquisition (radar, laser, lidar) [9] (p. 27)

This concept sets itself apart from approaches prevalent in large enterprises, that focus on full automation [6] (p. 73). Machine data are not considered, as the low degree of interlinking in production in SME [1] (p. 7) and the insufficient acquisition of machine and process data [4] (p. 37) not only not permits this, but also a drainage of core know-how is prevented. It is, however, also not required to collect detailed machine data for an intelligent and flexible production control, which is predominantly required in SME [3] (p. 44).

As the database of production data in SME is extremely heterogeneous, and its quality regularly insufficient for the realization of the Digital Twin, the following two main systems are introduced for data acquisition:

- sensor based tracking
- machine vision

This paper focuses solely on the concept. Technical solutions are not addressed and will be presented in further publications. Sensor-based tracking systems are commercially available. Extensive program libraries for the machine vision approach are existent. The dual system approach is a result of the great costs associated with a solely sensor-based procedure. Sensor-based tracking provides information regarding

- routes and position of production employees
- routes and position of large and highly mobile production devices, e.g. forklifters

The low numbers of mobile production devices and production employees compared to products allows a data acquisition via sensor-based tracking. Furthermore, machine vision relies on permanent employee and mobile production device visibility that cannot be ensured in production systems whereas product visibility is easy to obtain at production machines along the process chain.

Therefore, machine vision serves to identify products at the production machine. Through this, equipping every single product with a sensor or tag can be avoided. This results in a cost structure for data acquisition which is not proportional to the number of products tracked in the production system (Fig. 2). The approach is especially relevant if a high number of products is located in the production system or the product or process characteristic are not suitable for a sensor based tracking e.g. tempering. These obstacles are typical limitations in common production systems that can be avoided through machine vision. The image recognition also allows to detect and identify KLT (small parts container) using a numbering system, should this be required individually. In this context, picture recognition therefore is employed to

- detect and identify types of products at the production machines
- detect and identify small production devices and specific products, if individually required.

Table 1 demonstrates examples for performance indicators, that can be derived from the introduced data sources. The marked indicators (*) require small further measures, e.g. a visual marking or a specification of a transport device when defining the master data.

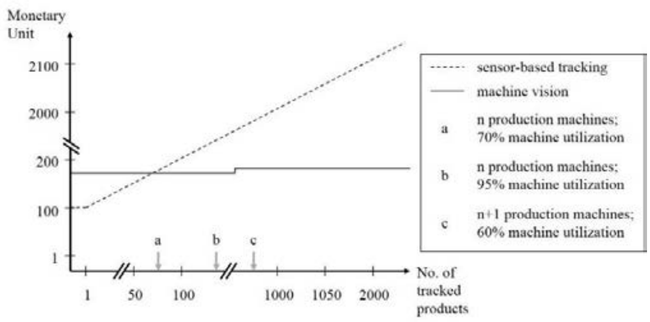


Fig. 2: Schematic cost development of sensor-based tracking and machine vision

The necessity for a standardization of data interfaces, therefore, is completely eliminated, as an autonomous system is installed. The realization concerning hardware is based on modules, that can be inserted easily and in the number required at relevant positions of the production system. Agility and scalability are marks of character of the presented concept.

Table 1: Selection of suitable performance indicators using data from sensor-based tracking and machine vision

Information	Sensor-based tracking	Machine vision	Combination
Product (type)	No	Yes	-
Product (specific)	No	Yes*	-
Cycle period	No	Yes	-
Production lot size	No	Yes	-
Transport/walking routes	Yes	No	-
Transport goods	No	No	Yes
Transport lot size *	No	No	Yes
Machine occupancy	No	Yes	-
Setup time / still-stand	No	No	Yes

3.2. Implementation of the Digital Twin

Having acquired the data within the production system, these have to be put to use. The location-independence of data acquisition and data evaluation is a core element, as, due to the low degree of knowledge in SME in the field of applications of industry 4.0 [3] (p. 3), a thorough evaluation cannot be expected, therefore is not desirable. Even in forerunner companies of industry 4.0, lacks of specialists and expertise are the main obstacles [4] (p. 57). Expertise in data evaluation and simulation are a core competence as such and will not be held available in SME. Applications in SME only require the results of the Digital Twin. Fig. 3 presents the implementation of a system that simultaneously demonstrates the separation of data to form a system-inherent data security. Herein, the separation of non-volatile and therefore non-real-time dependent data, such as

- ground plan
- layout
- purpose of the production machine
- parts list
- qualification of employees
- shifts etc.

And the volatile time dependent data such as

- production flow
- movements of employees
- machine assignment
- transport routes etc.

comes to bear.

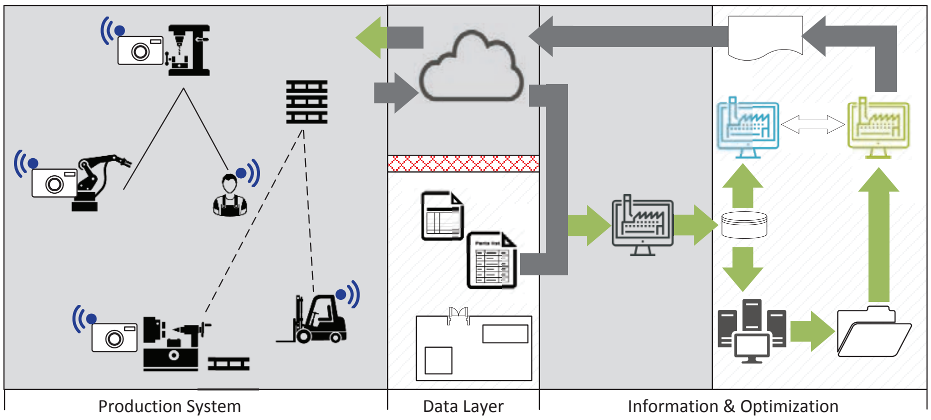
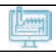
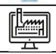
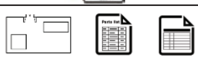
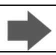


Fig. 3: Concept for the realization of the CPPS through the Digital Twin in SME

Table 2: Explanation of the concept scheme

Symbol	Explanation
	Digital Twin with optimized set of parameters; processes database and compares results with the Digital Twin to yield a quantification of the achieved optimization
	Digital Twin; linked to the database
	Digital Shadow; real-time linked with production system, generates database for the optimization
	Production machines
	Products
	Production employee with sensor-based tracking
	Production device with sensor-based tracking
——— - - - - -	Transport or walking routes
	Data transmitting machine vision module
	Master data, e.g. layout, part list, shift schedules etc.
	Cloud-solution
	Separation of volatile data and master data for knowledge protection
	Real-time capable components
	Non-real-time capable and necessary components; the time delay up until the results of the optimization are accessible is dependent upon the computing power available and the frequency of the data output. With increased computing power and data output frequency the real-time capability is heightened.
	Data flow
	Information flow
	Continuously updated database for simulation and optimization
	Optimized set of parameters for production control
	Optimization, parallelization possible
	Production control-improving recommendation

The separation of data and therefore gained data security is clearly visible. In the course of simulation, well proven software for production process assessment is used whose functionality can be easily extended with the aid of optimization software, if required individually. Detailed explanations will be given in further publications.

4. Conclusion and Outlook

In this paper a concept for the realization of the Digital Twin contribution to the development of a CPPS in SME is presented. The selected methods for data acquisition and evaluation mostly resort to existing isolated solutions. Stable operation and data acquisition is guaranteed. The improvement is the linkage of these isolated solutions to an overall system, that opens up completely new approaches in near real-time production control applications. Herein, automated as well as non-automated production processes can be subject to data acquisition, which is immensely important for mostly non-automated SME. No machine data is required, which allows for a full know-how protection. Moreover, the separation of volatile data and master data forms a system of inherent data security.

The next step is the development of a virtual production system, that generates data following the real production system with the two implemented data acquisition technologies. Based upon this, the data layer and the information and optimization section are constructed and verified trough testing. In the last step, the data acquisition hardware is implemented into a real model process and linked with the data layer. This forms the final and major step within the realization of the CPPS in SME as part of this concept.

5. Acknowledgements

The presented research work is partially financed by the European Regional Development Fund (ERDF) and the Oberfrankenstiftung as supporters of the project Oberfranken 4.0. The author is responsible for the contents of this publication.

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