Digital Shadows as an Enabler for the Internet of Production

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Abstract. Due to increasing atomization, manufacturing companies generate increasing amounts of production data. Most of this data is domain-specific, heterogeneous and unstructured. This complicates the access, interpretation, analysis and usage for efficiency improvement, faster reaction to change and weaknesses identification. To overcome this challenge, the idea of an “internet of production” is to link all kind of production relevant data by a data lake. Based on this data lake, digital shadows aggregate data for a specific purpose. For example, digital shadows in production planning and control help to manage the dynamic changes like delays in production or machine break–downs. This paper examines the existing research in the field of digital twins and digital shadows in manufacturing and gives a brief overview of the historical development. In particular, the potential and possible applications of digital shadows in production planning and control are analyzed. A top–down–bottom–up approach is developed to support the design of digital shadows in production planning and control.

Keywords: Digital shadow · Internet of production · Production planning and control

1 Introduction

The purpose of digital shadows (DS) is to provide all information needed to successfully perform a task and make a decision. The objective is to improve decision-quality and the performance of manufacturing. In practice the use of DS gains relevance as the quantity of information as well as the complexity of information systems increase and DS reduce the complexity for users by providing the relevant information [1, 2].

Advantages in information and communication technologies (ICT) enable companies to collect, use and store data to integrate the physical and the virtual world [3–5]. Using ICT enables e.g. virtual product and process planning or predictive maintenance [6, 7]. In many different industries the use of data analysis to support decision making is increasing [7]. Hence, a goal for producing companies is to identify an efficient way to use data and information [1]. In manufacturing, main benefits are a faster reaction to unexpected events and the identification of weaknesses in order to

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increase the efficiency of manufacturing [8]. This is of high relevance as manufacturing companies face challenges like increasing requirements of the customers on the products, rapidly changing markets, shorter product life cycles and sustainability [1, 4].

Manufacturing companies collect tremendous volumes of structured, unstructured and semi-structured data from different sources along the product life cycle [7, 9]. The increasing speed and volume of data collection simultaneously increase the challenges of data quality [9]. Additionally, in current manufacturing environment there are numerous domains that use different IT-systems, containing specific data and models [10]. This data is stored in different and redundant sources, is heterogeneous and hardly integrated. Therefore, access, interpretation and analysis of production data is difficult [9, 11].

Production planning and control (PPC) allocates activities of employees, production capacities and materials to fulfil customer orders. Therefore, PPC significantly influences the performance of a manufacturing system [12]. One challenge for PPC is the reaction to dynamic changes, e.g. operation times deviating from the plan or machines break-downs [13, 14]. Additionally, the necessary information is collected manually from different IT–systems causing delays, additional search efforts and missing information [3, 15]. Often PPC is dependent on the expertise of the planner [14]. However, even experienced decision makers cannot estimate the full impact of their decisions on the overall manufacturing system, which only achieves local optimization [16]. Therefore, the use of DS in PPS is promising to overcome these challenges and realize dynamic real-time PPC.

In Sect. 2, a literature review on digital shadows is conducted, including a distinction to the related digital twins (DT). Next, the application of DS for PPC and challenges and benefits are described. Section 4 summarizes and discusses the paper.

2 Literature Review on Digital Shadows and Digital Twins in Manufacturing

This section provides a general overview of the historical development of publications and definitions, applications and benefits of DS and DT in manufacturing.

2.1 Historical Development of Publications

In the field of engineering and computer science Google Scholar is the most extensive search engine [17]. Therefore, an analysis of metadata of publications extracted from Google Scholar gives an overview about the historical development of research. DS and DT are a relatively new research field. Prior to 2010, total 208 contributions to the topic DT and 291 contributions to the topic DS were published. Less than 100 each in the context of manufacturing. The development of new publications since 2014 shows that research on the topic of DT has grown strongly. The number of publications per year has grown from under 100 in 2014 to more than 4,500 in 2019. One main research focus is DT in production and manufacturing as Fig. 1. shows. In comparison, the number of publications on the topic of DS has only grown slightly, and has grown from about 100 in 2014 to more than 250 in 2019. The main research focus is also on DS in manufacturing, see Fig. 1. A related field of research is data storage e.g. in data lakes or data warehouses.

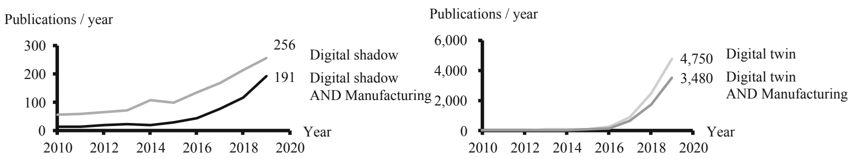

Fig. 1. Evolution of research on digital shadows and digital twins

2.2 Characterization of Digital Shadows in Manufacturing

The following paragraphs provide an overview of DS by describing different definitions, the main elements and benefits of DS. DS contain data traces and models [5]. Data traces consists of time-variant data and metadata like information about the source or recording time, which are needed for further data processing [1]. The data is generated by e.g. sensors or simulation and provided in domain–specific real-time [18]. DS contain both information about past and current conditions and provide information about future conditions [19]. DS provide near real-time data and information to enable an organization to control a permanently changing production [18]. When the system changes, DS are updated [5].

DS serve as a platform to integrate information from different sources to overcome semantic heterogeneity [9]. For this purpose, DS link data and models [20]. Data exchange between different domains improve the manufacturing, e.g. the manufacturer creates plant models which the operator needs when operating the plant. Typical tasks supported by DS are order processing, service or production planning. Since DS are task-specific, many different DS exist [13, 21]. Additionally, DS can be used through the whole product life cycle [20].

DS support decision makers and operators by providing the right information at the right place in the right quality in a sufficient way [1, 13]. As DS provide only the task-specific relevant data, the identification of necessary data, selection, aggregating and determination of granularity level of data are core part of designing DS [22, 23]. Data of past and current conditions is analyzed, e.g. for forecasts or simulations, to support decision making [19].

In conclusion a DS is a set of aggregated data traces and models providing the necessary information for a task. As the required information is provided in near real-time, DS enable a fast reaction to the dynamic and complex manufacturing environment.

2.3 Characterization of Digital Twins in Manufacturing

As in the previous paragraph, the following paragraphs provide an overview of DT by describing different definitions, the main elements and benefits of DT. Due to the increasing research in the field of DT, different definitions of a DT exist [24]. NASA provided the initial definition of a DT as “an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin” [25].

Likewise, many authors describe the DT in manufacturing as a virtual, computer-based complete representation or counterpart of a physical system which allows various analyses of the system based on real-time production data, e.g. [19, 26–29]. DT support the analysis of static and dynamic systems allowing real-time optimizations, decision support and predictions [27]. DT should improve and shorten production cycles and reveal inefficiencies [26].

The comprehensive literature review on DT by Kritzinger et al. (2018) emphasizes that in existing research the terms digital model, DS and DT are often used synonymously, as all are a digital counterpart of a physical system. Therefore, they are distinguished based on the data flow. Both DT and DS have an automatic data flow from the physical and the digital system. The data flow from the digital to the physical system is automatic for DT and manual for DS [6].

In the newest literature review of DT, Jones et al. (2020) differ between a virtual-to-physical and a physical-to-virtual twinning process. Changes in the physical or virtual entity are registered by metrology methods and lead to a change of the corresponding virtual or physical twin. Jones et al. identify reduction of costs, risk, complexity and reconfiguration time and the improvement of efficiency, decision making, manufacturing processes and competitiveness as perceived benefits described in literature and industry. However, these assumptions are often not based on quantitative evaluations [24].

Summarized, a DT of a manufacturing system consists of a physical and virtual part. Both parts are a complete representation of the counterpart allowing analyses of the original system. The aim is to support decision making and improve the production.

The objective of both DS and DT is to process data in order to support decision making. The comparison of DS and DT shows that they differ in the granularity of the data base. DT are a complete representation of a physical system, whereas DS only represent those parts of a system that are relevant for a specific task. In addition, a core element of DS is the linkage of data from different domains. In the following sections, the focus is on DS as they have similar functionalities as DT but require less data capacity and provide better decision support due to the task-specific information.

3 Application of Digital Shadows in Production Planning and Control

Based on the current research in the following section an approach for designing digital shadows is developed and specified using the example of PPC. Additional potentials of DS for PPC are further analyzed. PPC is chosen as an example because it is a core element in manufacturing companies [12]. Recent trends like volatile markets, increasing complexity and shortened product lifecycles also affect PPC [13]. Therefore, PPC must cope with increasing dynamic and complexity. Existing PPC systems, like Enterprise Resource Planning (ERP) system or Manufacturing Execution System (MES), support different tasks of PPC but the support in everyday, short-term decision-making situations could be further increased [16].

3.1 Approach for Designing Digital Shadows

To extend the existing research on DS a top-down-bottom-up approach to design DS in PPC was developed. The aim is to fulfill the information requirements of production planner and controller by providing the necessary information. As a result the PPC should improve through better decision support and reduced information search efforts. Therefore the information needed (information requirements) of the users are identified top-down. Additionally, the data base is described bottom-up to describe the information provided (information offers). In the following, this approach is presented in detail, Fig. 2 gives an overview of the approach.

Fig. 2. Top-down-bottom-up approach for designing DS

In the first step of the top-down analysis, the tasks in the PPC are analyzed to identify the user requirements. According to Schuh et al. the core tasks of PPC are production program planning, production requirements planning and production control [30]. At each of these tasks, production planners and controllers perform different sub-tasks with different requirements. The derived user requirements can be divided in functional and data quality requirements. All user requirements are documented in a specification sheet. In the subsequent user requirements analysis, the customer requirements are evaluated, classified and structured. This serves as the basis for the information requirement derivation. The user requirements are formulated as information requirements for the DS and entered in a requirements specification. This serves as the basis for modelling the information requirements. The result of the top-down analysis is a detailed description of the information requirements from the production planner and controller perspective.

At the same time, the data base is analyzed bottom-up to identify the information offers. For this purpose, the data base and different data analysis methods are investigated. In the first step data is described and characterized (in the context of PPC). The result is a morphology of PPC data describing the data type and context information like unit or change-frequency. In the next step, relations within the data are analyzed and described. The relations simplify the aggregation, linkage, selection and evaluation of the data in a DS. In the next step, suitable data analysis models are selected. First the properties of data analysis methods are described. Based on this, it is investigated which of the described data can be evaluated and how. The aim is to describe the possible analyses and to use them to derive the information offers. Based on the prior steps the information offers are modeled. The result of the bottom-up analysis is a detailed description of the information offers in the context of PPC.

All in all, this procedure enables the description of DS for all tasks of the PPC. These DS provide production planners and controllers with all information they need for their tasks, thus enabling them to make well-founded decisions.

3.2 Potentials of Digital Shadows for Production Planning and Control

The following paragraph analyzes the potential benefits DS offers for PPC. As DS provide real-time data, one potential is the ability to react to dynamic changes [13, 14]. Especially for scheduling of orders and production control DS enables task-specific decision support by data analyses [31]. One example for improving existing PPC systems is the lead time prediction as in [32]. The integration of historical and real-time data, static and dynamic data into PPC and the analysis by e.g. data mining methods increase the quality and reliability of planning results [8]. Additionally, the DS as single source of truth reduces efforts for manual data acquisition from different systems. [15] The targeted use of information from other areas in real time can improve the PPC [33]. The decision support for production planners and controllers can be increased by further analyses and simulation and considering a larger data basis [8, 14]. Another potential of DS for PPC is the development of an autonomous, self-controlling PPC [8].

In summary, the main advantages of DS are an improved decision support for production planners and controllers in short-term decision situations and the reduction of information search efforts and the provision of real-time information. An approach to design DS for PPC must describe how the information can be provided and derived from the data and models in such a way that it increases the decision quality.

4 Conclusion and Further Research

A DS is a set of aggregated data traces and models that provide necessary information for a task. This enables decision support in manufacturing with low latency times. The use of DS in the dynamic and complex PPC therefore offers several potentials for improvement, like enhanced decision support or reduced information search efforts. Additionally, a concept for designing DS in PPC was described. The concept describes a top-down bottom-up approach, with which the information needs and the information offers are linked.

In further research, the procedure for describing specific DS, e.g. in PPC, should be further detailed. Future research should also focus on the further development and application of DS for PPC in industry. This includes the modelling of data structures and information requirements.

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