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Development of Digital Shadows for Production Control

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Abstract

Production controllers have to make short-term decisions on the adjustment of production processes. Existing IT systems do not fully meet the information needs and functional requirements of production controllers and provide insufficient support for the decision-making process. The idea of Digital Shadows addresses this challenge by providing the user with the relevant information for a specific purpose consequently supporting the process of decision-making. This is achieved by linking, aggregating and analyzing production data from various sources.

In this paper, an approach for the development of Digital Shadows for production control is presented. The approach comprises the three levels of Digital Shadows for production control: 1) data offers, 2) information requirements and 3) analysis methods. To describe the data offers, the relevant data and data sources identified and categorized. The information requirements are derived from the decisions in production control. To link the data offers and information requirements the relations between the data and the tasks of production control are modeled. At the analysis methods level, existing production control analysis methods are examined and categorized. Additionally, an approach for the application of the analysis methods to the data is explored. The approach for the development of Digital Shadows was further on applied in order to create an exemplary Digital Shadow for production control.

Keywords

Digital Shadow; Production planning and control; Data analysis, Internet of Production

1. Introduction

Production control has the goal to realize the production planning under consideration of the dynamic production situation in the best possible way. [1] This significantly influences the performance of production and is therefore crucial for the success of a company. [2] However, production controllers face multiple challenges. A major challenge is a reaction to short-term changes and disruptions like sudden resource failures or deviations of the processing time from the plan lead time. The production controller must decide on appropriate changes to the production processes. [3,4] The effects of this decision's influence on the overall system can be hardly determined due to the high complexity caused by various interactions and dependencies in production. As a result, production control is often optimized only locally. [5]

Besides, external demands increase the performance requirements for production, which also affects production control. For example, customers require high adherence to delivery dates, short delivery times, and fast response to change requests which influences the logistic target values. Production control can influence the fulfilment of these demands, which requires a high flexibility of production control. [6,7] The demands for individual products and shortened product life cycles increase the complexity of production control, since the complexity of production control increases with the number of different orders and machines. [8,2]

At the same time Information Technology (IT) systems do not fulfil the increasing requirements of production control sufficiently. The IT systems do not contain all required information for a decision, why user manually create spreadsheets containing the relevant information. [9] Digital Shadows provide relevant information for a decision and thus represent a promising solution to overcome these challenges in production control.

Design and development of Digital Shadows is an objective of research within the Internet of Production, a German Cluster of Excellence at RWTH Aachen University. Digital Shadows collect, aggregate and analyse data from different sources to support the decision-making process. [6,10] For this purpose, the information required for a decision must be identified. [11] Information is generated by the application of analysis methods to aggregate, link and analyse the data. [12,13] Digital Shadows are a promising approach to improve a production system as they increase the decision-quality and provide users access to relevant information. [14]

The paper describes an approach for the development of Digital Shadows in production control. First, an overview of the theoretical background of Digital Shadows and Digital Twins is given. In section 3 related work on Digital Shadows for PPC is examined. Afterwards, the proposed concept for Digital Shadows in production control is illustrated. The application of the concept is explained in a use case. Finally, a conclusion on the current state is drawn with an outlook on future work.

2. Theoretical Background

In this section, the theoretical background on Digital Shadows is examined. This includes definitions and core elements as well as a comparison of both concepts.

A Digital Shadow consists of aggregated data traces and models. [15] The aim is to support the decision-making process. [14] For this reason, the right information must be provided in the right quality at the right place and at the right time. [6,16] For this purpose, the relevant information is generated within a Digital Shadow by linking, aggregating and analysing data traces using models. [17] A data trace consists of time-variant data and metadata. [12] A data-trace can originate from various IT-systems and are integrated by Digital Shadows. [18] The data-traces of a Digital Shadow describe both past and current states. [19] Changes in production create new real-time data traces. [15] Future states of the system can be derived from the application of simulation or prediction models. [19] As Digital Shadows are purpose-specific, different Digital Shadows exist. In production, they are used for e.g. production planning and order processing. [20]

NASA provided an initial definition of Digital Twins 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". [21] Current research often defines a Digital Twin as a virtual, complete representation of a physical system. [22,23,14,24] As a Digital Twin directly influences the physical system, a change of one system (e.g. virtual) leads to a change of the other system (e.g. physical). [25,23] Digital Twins analyse static and dynamic systems based on real-time production data. [26,19,24] A Digital Twin in production has the goal to optimize the production process by cost savings, efficiency increase and risk reduction. [25] In addition, a Digital Twin should support the decision-making process by analysing data and providing predictions. [27]

In summary, both Digital Shadows and Digital Twins support the decision-making process by providing information to the user. One difference is in granularity and scope. As a Digital Twin is a holistic representation of a system, it requires larger amounts of data and models than a Digital Shadow. A Digital

Shadow provides information for specific purposes, therefore only the necessary data and models are required.

3. Related Work on Digital Shadows in PPC

In this section, previous and related work concerning concepts for Digital Shadows and their use in the context of PPC are reviewed. Since Digital Shadows and Digital Twins contain similar elements, both approaches of Digital Shadows and Digital Twins for PPC are considered as related work. As of today, current research has barely addressed the design, use, and application of Digital Shadows for PPC.

Bauernhansel et al. [6] describe Digital Shadows for production as a macro-service providing the right information to the user. Various micro-services enable the functionalities of Digital Shadows. These are, for example, the collection of user requirements, the selection and compression of information and the control of the information flow. Four development stages of Digital Shadows are described: linkage of information, information flow control, information quality control as well as feedback and self-optimization of data and information basis.

The framework for Digital Shadows by Ladj et al. [28]consists of a virtual and physical system. The virtual part of a Digital Shadow is a data and knowledge management system. The knowledgebase is generated by the application of data analytic methods to the database. The information of the knowledgebase is used to support the decision-making process and to optimize the physical system. The Digital Shadow improves continuously, as it is self-learning. The application of the framework demonstrates improvements of the shop-floor performance.

Schuh et al. [29] model a data structure of Digital Shadows in the single and small batch production as a basis for a knowledge management system. The data structure is modelled based on a generic order fulfilment process in an Entity-Relationship-Model. The model visualizes the relationships between data and elements of the order fulfilment process. Considered data types are mater and transaction data of a production system based on the required information in the different departments of the order fulfilment.

Agostino et al. [30] describe a Digital Twin approach for PPC, which is based on a cyber-physical production system. The Digital Twin is a virtual representation of the production system. It consists of a simulation-based optimization model and functions triggering the simulation. The appliance of the results of the simulation optimizes the production system. Improved performance of production scheduling is demonstrated in a use case at an automotive supplier.

The approach by Schuh et al. [14] describes a top-down-bottom-up concept for designing Digital Shadows for PPC. Relevant information for the decision-making process in PPC is modelled top-down as information requirements. The information offers provided by analysing data with analysis models is modelled bottom-up. The concept helps companies designing Digital Shadows and applying them for PPC.

Kunath and Winkler's [5] conceptual framework of a decision support system for the order management process is based on a Digital Twin. The relevant data for order management is derived from different information systems. A suitable model regarding the data and decision is chosen by an automatic model generator. If no model is suitable a new simulation model is generated. Algorithms supporting the decision-making process evaluate the results of the simulation model. Possible applications of the framework are dynamic scheduling or dynamic pricing.

4. Digital Shadows for Production Control – Concept and Application

This section presents an approach for Digital Shadows for production control. First, a concept of Digital Shadows describing the elements and their relations is presented. Based on this, the three core elements data offers, information requirements, and analysis methods are specified by the application in a use case.

4.1 Concept of Digital Shadows for Production Control

The concept for Digital Shadows consists of three levels: data offers, information requirements, and analysis methods. By connecting the levels, Digital Shadows can provide the necessary information and thereby support the decision-making process. Figure 1 gives an overview of the concept of Digital Shadows. On the information level required information is determined. At the analysis methods level, the information requirements are transformed into data requests. The requested data is provided by the data offers level. The application of analysis methods on the data generates the required information and provides it to the users.

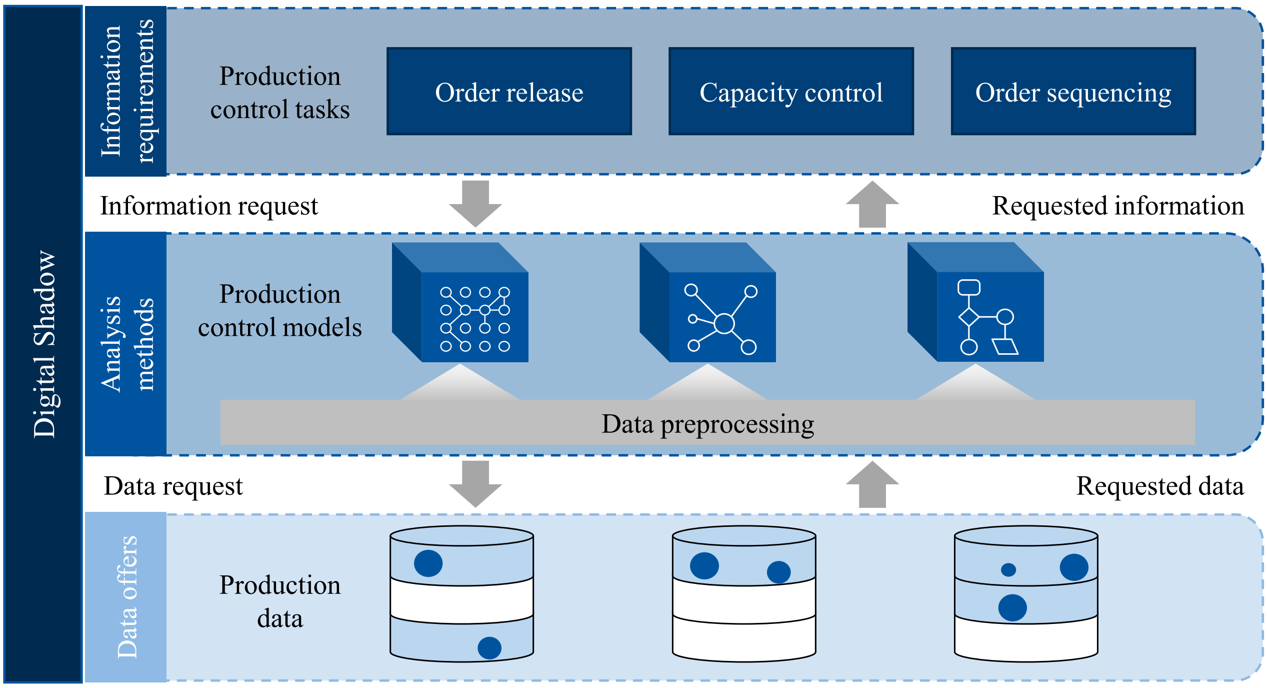

Figure 1 Concept of Digital Shadows for production control

The lowest level represents the data offers. On this level, data and relations between data are described. To model the data offers, elements of production relevant for production control are described and modelled. Relevant elements are e.g. orders, machines, personnel, and material. A Systems Modelling Language (SysML) based Block Definition Diagram (BDD) and Internal Block Diagram (IBD) can be used to give an overview of the elements and the relation of the elements. The production elements are the blocks of the model. Attributes describe the characteristics of the production elements. For production orders, attributes are e.g. delivery date, start date, product number and work schedule.

The data of each attribute is stored in the IT systems of a company. Both IT systems with a direct and indirect link to production control are possible data sources. IT systems with a direct link to production control are PPC systems, like Enterprise Resource Planning (ERP), Manufacturing Execution (ME), Advanced Planning and Scheduling (APS) systems. IT systems with an indirect link to production control are systems from other domains, such as development or purchasing, which contain relevant data for production control. These are e.g. Computer Aided Design (CAD), and Product Lifecycle Management (PLM) systems. As the IT system configuration is company-specific, the focus of this work is not on a generic description of the relationship between the IT system and data.

Data-specific features describe the data. These features contain information about e.g. source, type, quality, and generation frequency of data. The data offers are the foundation of Digital Shadows. They define the limits of the information generated by Digital Shadows in the current system configuration. If further information is needed to support the decision-making process, additional data must be collected and stored.

At the top level, the information requirements in production control are modelled. First, the decision-making requirements are derived from the tasks in production control. To realize the production plan, production control must initialize, monitor and adjust the production. The related tasks are e.g. order release, capacity control, and order sequencing. [31] Each of the tasks requires at least one decision from a production controller. For example, order release decisions determine the start and sequence of order release to the production. For each decision, the necessary information is determined and converted to information requirements. During the order release, information like delivery dates of open orders, and availability of resources and materials are required. Depending on the production control level (e.g. production network, unit, machine) different information is required.

The dimensions of information quality, type and quantity characterize the information requirements. Information quality describes the necessary accuracy, completeness and consistency. Information types range from descriptive, past-oriented types to predictive, future-oriented types. Information quantity describes the minimum viable data set to support the decision. [32] The modelled information requirements specify the information provided by the Digital Shadow through the model-based analysis of the data. The modelling of the information requirements thus represents the specifications for the digital shadow.

At the middle level, analysis methods connect the top and bottom level of Digital Shadows. Data is preprocessed and production control methods generate information. In this context, production control methods are mathematical models that generate information from existing data via e.g. simulations, optimizations or AI-based analyses. One example is the prognosis of the lead time based on master and transaction data like in [33–35].

Existing production control methods are classified based on their characteristics. Characteristics of the methods are input data, output information, and analysis type. The input data specifies the data type, necessary data quality and quantity, as well as the aggregation level of data. The output information specifies the information type, accuracy, and ease of interpretation. The analysis type describes the logic, e.g. simulation or neural network, the scope, e.g. prescriptive or predictive, as well as the properties, e.g. calculation duration, and traceability. By matching information needs and the data offers with the input and output variables of the production control models, suitable models for the specific decision supports can be identified.

Since the raw data from the system often does not meet the data quality requirements of the methods, the data is first preprocessed. This includes data integration, data cleaning, data normalization and data transformation. Data integration merges data of different sources to one data set. Data cleaning is necessary to correct and filter the wrong data. Data normalization and transformation adapt the convert the data into a form suitable for the production control model. [36] The Digital Shadow can then apply the models on the preprocessed data to generate the required information supporting the decision-making process.

4.2 Application of Digital Shadows for Production Control

The concept for Digital Shadows of production control described in section 4.1 is applied to a use case at the Demonstration Factory Aachen (DFA). DFA is a make-to-order manufacturer located in Aachen.

Since Digital Shadows are task-specific, an explicit Digital Shadow of production control is described. The focus of the use case is on decisions regarding short-term capacity adjustments in the context of capacity control. These are e.g. ordering of overtime as a reaction to disturbances like a resource failure. The production controller needs information about the configuration, costs and logistical target variables (adherence to delivery date, lead-time, capacity utilization and inventory [1]) of a future capacity scenario. The digital shadow must therefore provide future-oriented information on capacity scenarios in a second-by-second resolution. The observation period varies case-specifically from 1 day to 1 week.

The relevant elements of the system are the areas, such as logistics and production areas, machines, personnel, products, orders, material and IT systems. The IT systems are the source for the data of the individual attributes. Existing data sources are the ERP system as well as sensor data that collect electrical data. Figure 2 displays the elements as well as the descriptive attributes of the SysML BDD. The elements are production orders, products, machines, IT-Systems, personnel, material, transport vehicles and area. The attributes start-, end- and desired-date, work schedule, customer, order and product number, quality, and current state describe the production orders. The product number links every production order to one product. The attributes describing a product are product group, BOM, and work plan. The work plan defines which capacities are required to fulfil a production order. The work schedule defines when the capacities are used. Personnel and machines are the capacities to fulfil the production orders. Machine group (e.g. laser cutting, saw), hourly wage, number of workplaces, shift, wait-time, lay-time as well as electrical power and currency describe the machines. Personal group (e.g. assembly, welding), qualification, shift and hourly wage characterize the personnel. Attributes characterizing the material are material type, costs, number, stock location, quantity in stock, supplier and supply time. The BOM links each production order to the required material. Transport vehicles transport materials and products within the DFA. The vehicle type (e.g. forklift, electric crane), transport speed and quantity as well as the availability describe them. Relevant attributes for areas are size, required personnel and area type like storage, production or assembly. Either the ERP-system or sensors provide the data. For the task of capacity control, not all modelled data is necessary. Only the data used by the analysis methods are required.

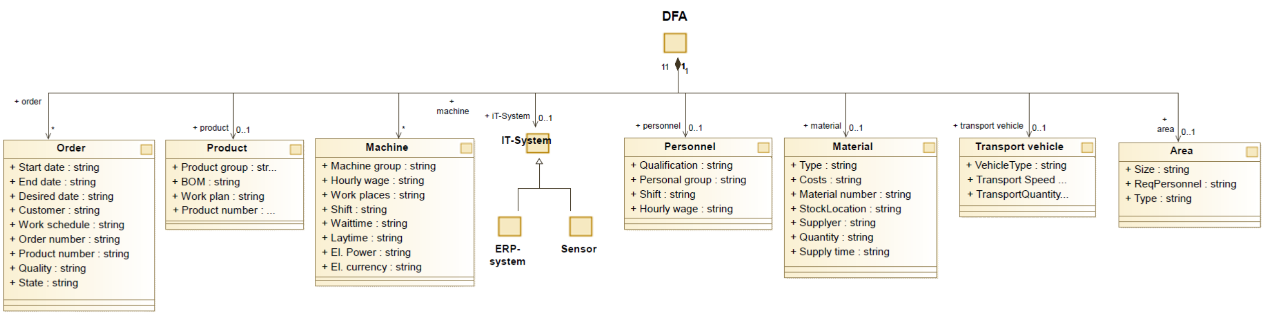

Figure 2 Block Definition Diagram of elements and attributes of DFA

To fulfil the user's information requirements, suitable analysis methods must be identified. To support the decisions of capacity control the Digital Shadow must calculate and evaluate different capacity plans. As a simulation can calculate and evaluate different production scenarios, it fits the requirements best. It is used as an analysis method for this use case. The simulation determines the occupancy of machines and personnel by orders in the simulation period under consideration of material availability (here between 1 day and 1 week). Required data are the available capacities of machines and personnel as well as the required capacities of production orders. The possible processing time for a production order is limited by material availability and the planned start and finish dates. A calculated capacity plan is then evaluated regarding costs and adherence to logistic targets. Data of machine and personnel costs are required. Table 1 gives an overview of all required data for the simulation and the related attributes of the BDD.

The simulation calculates and evaluates different scenarios with different capacity configurations. The results are information on possible capacity plans with their costs and logistical target values. The Digital Shadow provides this information to the user supporting the decision-making process of capacity controlling.

Table 1 Required input data for simulation model

Production element	Required data for simulation model	Attributes in BBD
Machine	Available capacities	Shift plan
	Machine costs	Hourly wage
Personnel	Available capacities	Shift plan
	Personnel costs	Hourly wage
Order	Possible processing period	Planned start date
	Possible processing period	Desired end date
	Allocation to product	Product number
Product	Required capacities	Work Plan
	Required material	BOM
Material	Availability material	Availability

In summary, the Digital Shadow enables production controllers to evaluate different capacity scenarios and decide on the best scenario according to the current targets. This increases transparency and improves the target achievement.

5. Summary and Outlook

The dynamic production environment as well as increased demands in production control require an improved decision-making process support for production controllers. The concept of Digital Shadows is a promising approach to provide the user with relevant information. In this paper, an approach for developing Digital Shadows for production control is presented. The three levels of the proposed concept are data offers, information requirements and analysis methods. The analysis methods link the data offers with the information requirements by generation the information based on the offered data. The concept is applied to a real-world use case at DFA. The developed Digital Shadow supports decisions of capacity control.

In comparison to existing IT systems for PPC, the Digital Shadow provides all required information for a decision in production control. Data of different systems and domains are aggregated to the required detail level. Additionally, Digital Shadows use task-specific, in-depth analysis methods generating detailed information. In conclusion, the Digital Shadow provides the relevant information for a decision improving production control.

The presented approach focuses on one use case. In further research, more use cases and the application of the concept at different companies can be addressed. In the actual configuration of the Digital Shadow, users choose the scenarios. In future realizations, an AI can be integrated to generate scenarios. In addition, the linkage of different production control models to generate information can be further examined.

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Biography

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