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Procedia CIRP 104 (2021) 1269–1274

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54th CIRP Conference on Manufacturing Systems

A Framework for Digital Twins for Production Network Management

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Abstract

The dynamic and highly complex task of production network management requires decision support through quantitative models. In the industrial praxis, these models are specifically designed and implemented for particular management decisions, requiring significant one-time effort for model creation. This contribution utilizes the digital twin concept to facilitate production network models that are continuously synchronized with the examined production network to support several different management decisions. The approach structures data from existing information systems as a synchronized generic base model, which is used to create problem-specific executable models, thereby saving costs through repeated model use and quicker decision making.

Keywords: Digital Twin, Production Network, Modeling

1. Introduction

In today's environment, producing companies face many challenges that require quick, decisive, and accurate decision making. Most of these companies operate global production networks consisting of several production sites around the world [1]. Due to these networks' ever-changing requirements referring to markets, factor costs, and political and legal factors, the networks have to be continuously adapted [2]. However, the complexity of the managerial decisions in production networks requires quantitative tools, ranging from data analytics through simulation and optimization to artificial intelligence [3]. Some of these tools, typically those used for regular decision-making processes, have been institutionalized and are used on a regular basis. Most decision-making support tools for strategic one-time decisions are developed, implemented, validated, and used only once, which binds multiple experts and can take months [4]. Due to this delay in model creation and use, only long-term decisions with an appropriate preparation time can be supported with these models. The time constraints may even negatively influence experts' ability to validate and verify the models before use, leading to inaccurate results [5].

A possible solution for this issue is the digital twin concept. Digital twins denote the model-based representation of all aspects of a system [6]. In digital twins, a model complex of multiple interconnected models is used to describe the considered system. These models are constantly synchronized with the real system, allowing for the accurate prediction and even model-based control of systems [7]. One of the first applications of digital twins was shown by NASA controlling complex aircraft [8]. Today they find increasing application in production systems, for example, to facilitate predictive maintenance, enable autonomous transportation fleets, and allow human-robot collaboration [9]. They are also used to plan and control production systems, but have not yet been widely discussed for global production networks. This contribution proposes a conceptual framework for developing and using digital twins of global production networks to facilitate decision-making. The framework describes a general structure, methods for model creation and synchronization, types of applications, and use cases for the digital twin. It represents the outline of a digital twin that will be detailed further in future contributions.

The remainder of this contribution is structured as follows: Section 2 provides an overview of relevant fundamentals and

10.1016/j.procir.2021.11.213

the state of the art. Section 3 presents the general structure of the conceptual digital twin framework followed by a detailed discussion of the different aspects of the framework. Finally, section 4 provides a conclusion and discusses avenues for future research.

2. Fundamentals and State of the Art

This section discusses relevant contributions to the state of the art of digital twins for global production networks. First, tasks within the management of global production networks are discussed. Second, exisiting types of quantiatative decision support tools are examined, as the digital twin can combine several of them. Finally, existing approaches to create a digital twin for configuration focused management decisions in global production networks are presented.

2.1. Management Tasks in Global Production Networks

The core tasks in global production management can be separated into strategic, configurative, and coordinative tasks. Strategic tasks describe the definition of the production strategy in accordance with the business strategy. These decisions are long-term and act as guidelines for the next two categories. Configurative tasks directly impact the physical structure of the production network. These are medium- to long-term decisions depending on the aspects of the structure that are changed. Coordinative tasks control the operative processes and product, material, and information flows in the production network. Decisions in this category are short to medium-term. [10]

Many strategic tasks do not benefit much from the use of dedicated quantitative tools due to the degree of vagueness in these decision. Configurative and coordinative tasks, are more conductive to the application of these tools. Many coordinative task occur frequently and are well supported by existing decision-support systems. By contrast configurative tasks are typically less frequent and not supported with established tools. Thus, the framework and remainder of this contribution focusses on configurative decisions. For the purposes of this contribution, those tasks can be distinguished into network design, product and process allocation, and capacity and capability planning.

Network design tasks, which may include the restructuring of the production network in its totality, the selection of new production locations, or the consolidation of existing sites, are irregular decisions that involve multiple functions of a company. The objectives pursued with such projects lie within the realm of production, like reducing costs and working capital, shortening lead times, or increasing resilience. Other objectives require interaction with other functions, such as decreasing environmental impact and improving product quality. Some lie outside of the influence of production network management, such as improving brand recognition, increasing service, or capturing new markets. [10–12]

Depending on the particular company's development cycles, product and process allocation tasks are more regularly performed. They are triggered by newly developed products or production processes and determine where value creation processes should be situated under incomplete information regarding the new processes' costs. In these decisions, the network's production sites are typically assumed as fixed while the investment in equipment and personnel is evaluated. [13]

Capacity and capability planning processes are similar to the previous category but appear even more regularly as they are typically part of the reoccurring planning processes. Here, the production capacities and process capabilities of the sites are planned based on projections of future demand. In this category, the degree of knowledge regarding process characteristics is higher than in the previous category. [14]

2.2. Quantiatative Decision-Support Tools in Global Production Network Management

Several different quantitative decision-support tools have found application in global production network management. Generally, models can be separated into descriptive, explanatory, predictive, and prescriptive models depending on the type of use. Descriptive models merely represent a considered system describing its relevant attributes. Explanatory models explain the relationships within a system, whereas predictive models can infer future system states and behaviors, given a set of inputs. Finally, prescriptive models determine an advantageous system configuration given a set of objectives. [15]

Descriptive models in production networks include the commonly used information systems such as enterprise-resource-planning (ERP) systems, product-data-management (PDM) systems, product-lifecycle-management (PLM) systems, computer-aided-quality (CAQ) systems, and several others. Another noteworthy descriptive decision-support model type is the key-performance-indicator (KPI) dashboard. These dashboards are used as a monitoring tool to guide decision making and trigger improvement projects. [16, 17]

Explanatory models used in production network management are analytical tools that are sometimes aggregated under big data analytics. These are used to examine and understand relationships between influences and the production network's performance. For example, analytical tools help to understand the relationship between outside events and demand fluctuations, cultural influences and worker performance, or product configurations and processing time. [18]

Predictive models are commonly used to project future influences like demands and material prices. For this purpose, a wide range of methods has been developed, from regression and meta/modeling methods to several simulation techniques like system dynamics simulations (SDS), agent-based simulations (ABS), and discrete event simulations (DES). Predictive models are also used to predict the behavior of production networks themselves. A range of model types exists, from time-invariant mixed-integer modeling approaches, either asset or resource-based, to time-variant DES to reflect the systems' behavior in different scenarios. Predictive models are often combined with comprehensive scenario analysis to infer configurations' performance for a range of future developments and determine Pareto efficient set-ups. [17]

As mentioned before, prescriptive models determine a favorable configuration given a set of objectives and conditions. Two types of methods can be distinguished, heuristics and opmization methods. Heuristics quickly find beneficial solutions but do not guarantee optimal solutions. Optimization methods determine the absolute best solutions, but require particular problem formulations. Both have found application in the previously described tasks of production network management. However, they are hindered by the necessarily reductionist nature of problem formulation that neglects aspects of the problem that do not lend themselves to quantitative descriptions. Thus, prescriptive models are often used in conjunction with more comprehensive predictive models, only solving parts of the overall problem. [19]

2.3. Digital Twins in Production Management

"A digital twin is the computerized counterpart of a physical system" [6]. The digital twin consists of one or multiple models reflecting the system's behavior based on domain knowledge and parameters describing the system's state. The distinction of a digital twin from a regular model is in the comprehensiveness of the representation and the synchronization with the real system [20]. The synchronization is facilitated by capturing data from the real system at all times, structuring that data, and feeding it to the digital twin. This data is referred to as the digital shadow [21].

In production systems, digital twins have found increasing application in the last years. Typically, the digital twins are bound to a specific asset or a product. Digital twins describe the state of production machines, the manufacturing process of complex products, internal logistic fleets' actions, and the control of entire production systems [7, 9, 22]. The extensive application of digital twins is only possible due to increased connectivity under the influence of industry 4.0 [23]. Increasingly, assets and products are connected to digital information systems, and sensors capture more aspects of production systems. The trend towards digitally connected devices in production is broadly discussed under the term cyber physical systems [21]. Combining all these systems' data can result in a digital shadow of production systems enabling various applications. Several works have proposed partial digital twins or product or process twins to improve production network management. Other works, on the contrary, have discussed the possibility of using a model framework for multiple applications through problem-oriented abstraction [4].

While a wide variety of models and methods has been discussed to support production network management decision [19], these models are focused on one decision type and result in one time uses. The existing approaches to use models continuously and in the form of digital twins are focused on regularly occurring decisions.

3. A Conceptual Framework for Digital Twins of Production Networks

The irregularity of many management tasks in production network management has so far limited digital twins' use. Digital twins can provide significant benefits when used regularly by enabling use without extensive modeling. Additionally, the models' continuous updating allows better model quality through dedicated calibration processes built into the models. However, as many of the previously discussed adaption tasks are one-time decisions, the impetus to create institutionalized digital twins is low. Therefore, this contribution proposes a novel digital twin framework to utilize the benefits of institutionalized decision support tools for irregular decision types. This digital twin, illustrated in Fig. 1, will facilitate better and faster decision making, and help companies to react to the ever changing conditions.

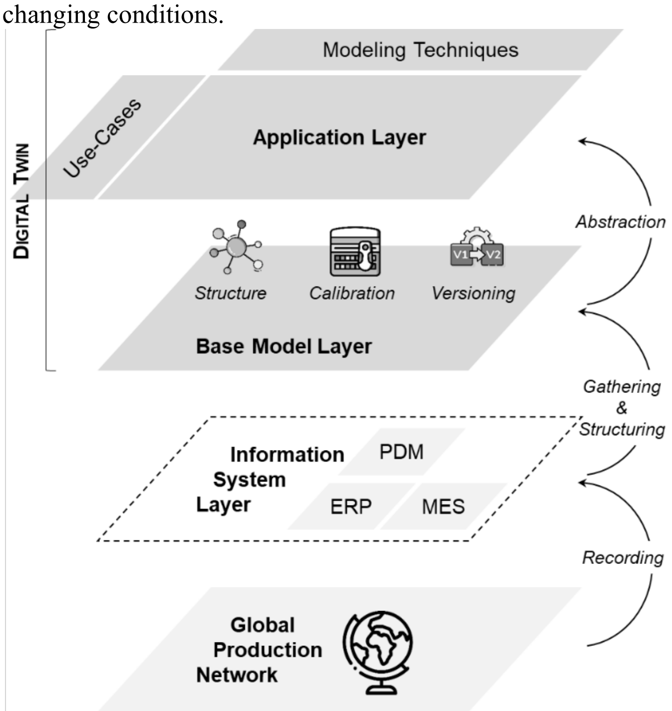

Fig. 1. Overall structure of the digital twin for production networks

The integration of multiple decision-support models is facilitated by the separation of specific models from the digital twin's backbone. Fig. 1 illustrates that the digital twin is separated into a base model and an application layer with several problem-specific models. The base model represents the production network and structures relevant data points according to universal object types. It is created using data stored in the existing information systems of the company and its partners. It facilitates the digital twin's continuous updating and enables an archiving function that allows the application layer to access the network's older states. The application layer consists of a multitude of different models that are modular and serve various management tasks. The two lower layers shown in Fig. 1, represent the production system itself and the information layer, which consists of the range of relevant information systems employed by the focal company. The different models the digital twin offers can be used in several use cases outside of the common optimization of a single problem solution.

This new framework will enable the continued use of quantitative methods for production networks. The novelty of this approach lies in the separation of the model base layer and the application layer in conjunction with a set of different problem specific application models. Previous approaches to use quantitative models in global production networks either focused on a very specific type of problem or on generalist models that require significant adaption to be used for different problems [13, 14]. Furthermore, the digital twin concept has been explored by several others focusing on products, machines and shopflor [6, 7], while it has received much less attention on the network level. The following sections discuss the aspects of the here proposed framework in more detail.

3.1. Information System Layer and Data Acquisition

Several information systems are connected to the digital twin. They include standardized systems as well as proprietary systems only found in particular companies. For the application in a digital twin, the systems' data quality, data granularity, and updating cycles are considered. For the technical implementation, the accessibility of data is essential. In the following paragraphs, the primary information systems serving as data sources for the digital twin are discussed. Fig. 2 displays the systems discussed here and the information types these systems can provide for a digital twin. The information types presented here in the upwards pointing arrows reflect typical information that can be important for the digital twin. Which of these are relevant depends on the selected applications and the data available at the company.

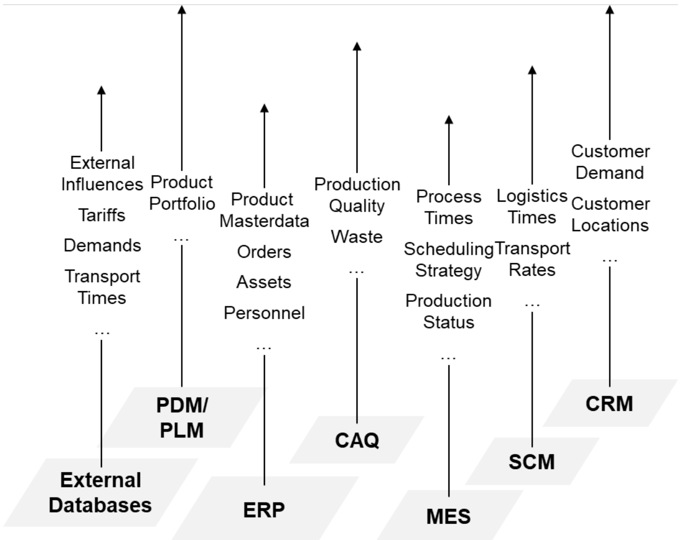

Fig. 2. Core information systems for digital twins and their information types

ERP systems present the leading source of information for the digital twin, as most configurative tasks are at least partially cost-focused. ERP systems store information with immediate reference to financial aspects of a business. Additionally ERP systems store master data describing the structure of products in the bill of materials (BOM). The digital twin utilizes ERP systems as the primary datasource supplemented by other systems informations.

MES, as well as logistics management systems, are considerably closer to the operative business in production and logistics and capture data regarding these processes in higher granularity. These systems can be a valuable source to refine the parametrization of the modeled production processes. And validate masterdata stored obtained from ERP systems.

PDM and PLM systems contain information centered on the product. The information in these systems is created manually by product designers. These systems provide information regarding detailed product variants to the digital twin.

Auxiliary systems like customer-relationship-management (CRM) systems, computer-aided-quality (CAQ) systems, and supply-chain-management (SCM) systems may contain additional data regarding influences on production systems. By integrating them with the digital twin, more information regarding specific demands, process quality, and supply situations can be gathered.

Information systems owned by partners may be accessed based on existing contracts to coordinate the supply chain. Interesting information includes available capacity and projected processing times at suppliers as well as demand forecasts of customers. These data can only be integrated through specifically designed interfaces coordinated with the partners in the value chain.

External sources of production-related data may enable a more comprehensive description of the production network. External sources may be databases for market developments, tax and tariff databases, logistics monitoring systems, resource market monitoring systems, employee availability databases, and others. These external data sources are connected to the digital twin based on the specific needs of particular decision problems. Additional data may be obtained by implementing data acquisition systems, such as a traceability system that captures product-related information.

3.2. Base Model Layer and Time Variance Process

As indicated before, the base model plays a central role in the digital twin. It aggregates information from the information system layer and structures it to enable access by the application layer. Additionally, the base model is responsible for the system's variance over time, i.e., data calibration and the structuring of system states. The following paragraphs discuss the structure of the base model and its different functions.

The base model uses an ontology of production networks to structure information from multiple data sources. Depending on the company and use case either existing ontologies such as the CDM-Core ontology ,for example, can be used and extended, or a company specific ontology can be created. The classes within the ontology reflect the physical structure of production networks closely. The specific instances and their parameters are created automatically by the base model by crawling the available data sources. Fig. 3 displays key classes represented in the base model. The base model can be extended to facilityte new applications by adding new classes and parameters to the ontology.

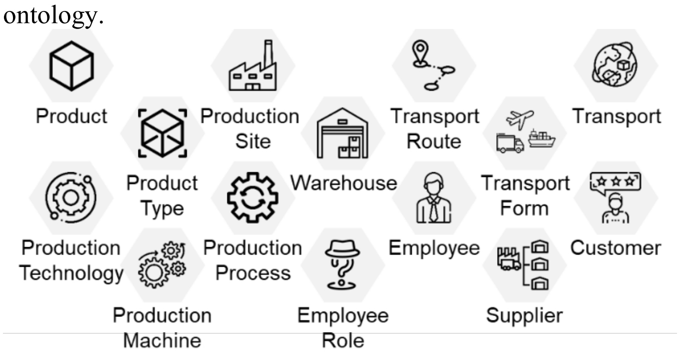

Fig. 3. Key classes of the base model

Each parameter type of an object is connected to one or multiple data sources using a particular processing method. These processing methods can be the simple referencing of a data point, the averaging of multiple points, or more sophisticated processes that consider multiple sources. Here technologies like process mining play a critical role in modeling characteristics of often repeated processes. For example, a production process can be characterized by analyzing and aggregating information about all of its occurrences. The creation of new data points may also trigger the creation of new object instances.

Calibration mechanisms within the base model can ensure the data quality of the model. These mechanisms utilize multiple data sources and compare their values to determine whether any data point is likely to be false. An example of this concept is checking the nominal processing time of a particular production step specified in the BOM by comparing it to actual processing times recorded in the MES. Depending on the magnitude of deviation, either automatic correction can be triggered, or manual assistance is required. The calibration mechanism can also detect changes in the system using a process mining approach when these changes are not reflected in the master data. In that case instance-based data points are compared with the existing master data and significant and sustained deviations from the master are detected. These changes can include shifts in average processing times, changes in worker availability or different order scheduling strategies.

One of the main issues of continuously used production network models is assuring the up-to-dateness of the model. Also, it can be beneficial to access older states of the network and experiment with them in some circumstances. In the base model, both object types and parameters can be marked as "state-relevant". Changes in objects like 'product' or 'production process,' which frequently change without constituting a change of the network itself, are not considered state-relevant, while types like 'production equipment' are state-relevant. Any change in a state-relevant object or parameter creates a new network state in the base model. The old version of the network is then archived. Over time, older versions can be clustered to save data and only store the most relevant production network changes. The application layer can access the different states of the network stored in the base model. Fig. 4 shows the base model's general functionality and its connections to other aspects of the digital twin.

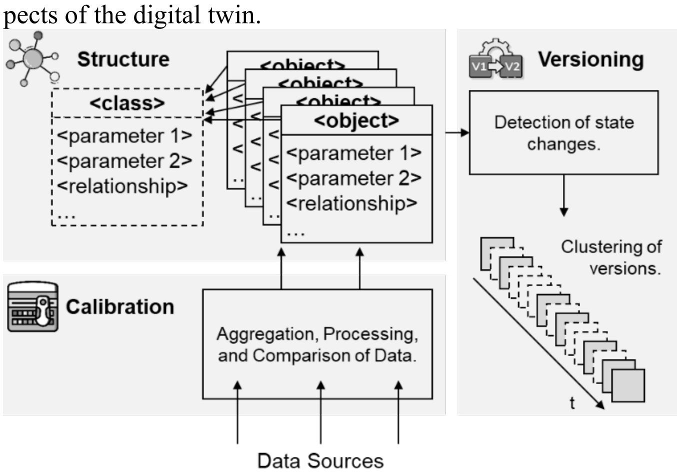

Fig. 4. Overview of the base model

3.3. Application Layer and Abstraction Process

Whereas the base layer facilitates the digital twin, the application layer represents the connection to its users. The application layer offers several models and methods to support decisions in production networks. These methods can range from relatively simple mixed-integer models to DES, optimization, and artificial intelligence. The application layer is structured in a modular fashion, allowing users to create different types of applications on top of it. The following paragraphs explain the overall functionality of the application layer and its different aspects in detail.

When creating a new application, the users determine a mode, an associated method, the considered part of the system, and the experiment's objectives. If possible, the system then creates an application that can be adapted according to the user's wishes. For this application built that requires an abstraction process of the base layer, the abstraction process proposed by Benfer et al. can be utilized [4]. The user can also choose to calculate different scenarios by adapting outside parameters. Fig. 5 shows the application creation process in detail.

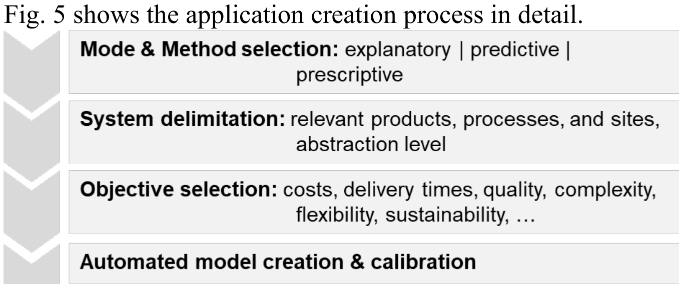

Fig. 5. Application model creation process

The application modes refer to explanatory, predictive, or prescriptive modeling of the network. Several modeling techniques are available for each mode, as shown in Fig. 6. To effectively use the models and limit computational times, it is crucial to precisely delimit the scope of interest. That means that aspects of the system irrelevant to the current problem can be simplified. Additionally, the examination can be limited to a relevant part of the network, for example, by abstracting upstream production processes, excluding certain aspects of the product portfolio, or not considering some production sites. The application builder then limits the degree to which these aspects are modeled as much as possible while retaining accuracy in the rest of the model.

Explanatory Models	Predictive Models	Prescriptive Models
• Cause-Effect Models • Cluster Analysis • Relative Key Performance Indicators • Historical Regression Models	• Multi-Period Mixed Integer Models • Discrete Event Simulation • System Dynamics Simulation • Markov-Chains	• Optimization • Evolutional Algorithms • Simulated Annealing • Deep Neural Networks

Fig. 6. Model types and affiliated model techniques

Finally, when creating an application, the user needs to determine the relevant objectives of the examined problem. These objectives may include specific production goals like cost reduction, reduction of bound capital, delivery times, and quality rates, but also system complexity, uncertainty and risks, sustainability, and greenhouse gas emissions or others.

After the model creation, it can be calibrated using the base model's recordings ensuring it provides accurate results.

3.4. Potential Use-Cases for the Digital Twin

Several use-case types for the digital twin exist. Here, four types of use-cases enabled by the digital twin are discussed in detail. Additionally, the benefits the digital twin provides for these use cases is highlighted.

Issue-based use describes the classical application of quantitative models in production network management: A specific problem is identified, and an ideal solution for this problem is required. In this case, a specific prescriptive or predictive model can be designed to examine the problem closely. The much-shortened turnaround time of models using the digital twin allows more iterations of the model to consider factors from other company functions that the model can not represent. Also, situations where decision times are shorter, like disruption events, could be supported using the digital twin.

Exploratory use describes employing an existing model to find beneficial configurations or see how the system reacts to external changes. This type of use requires a model that exist prior to the decisionmaking process, but may give decision-makers an improved understanding of their production network and its behavior.

Diagnostic use defines using models to replicate a past situation and explain the observed behavior of the system to deduct knowledge regarding future behavior and to target change processes within the production network.

Alerting use means creating a model that continuously runs in the background and triggers an alert when changes to the real system result in a predetermined unwished state or behavior. Based on this alert, projects to change the configuration of the network and adapt it can be started.

4. Conclusion and Outlook

This contribution proposed a framework for a digital twin of production networks. The digital twin consists of two primary parts, the base model layer and the application layer, facilitating its utility for several management tasks in global production networks. The framework can serve as an outline of digital twins and may act as a discussion point for digital twins in production network management.

Future works need to examine the role of calibration for such twins more closely, consider different application model types in conjunction with the digital twin, and discuss integration strategies for digital twins within the organization. Furthermore, inter-company aspects of such digital twins need to be studied more closely.

Acknowledgments

Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – 432466774 and the German Federation of Industrial Research Associations - 20907 N.

References

[1] Jacob, F., Strube, G., 2008. Why Go Global? The Multinational Imperative, in *Global Production*, Springer Berlin Heidelberg, Berlin, Heidelberg, p. 2.

[2] Lanza, G., Moser, R., 2014. Multi-objective optimization of global manufacturing networks taking into account multi-dimensional uncertainty. CIRP Annals-Manufacturing Technology *63*, p. 397.

[3] Lanza, G., Ferdows, K., Kara, S., Mourtzis, D. *et al.*, 2019. Global production networks: Design and operation. CIRP Annals *68*, p. 823.

[4] Benfer, M., Ziegler, M., Gützlaff, A., Fränken, B. *et al.*, 2019. Determination of the abstraction level in production network models. Procedia CIRP *81*, p. 198.

[5] Sargent, R.G., 2004. Validation and Verification of Simulation Models, in *Proceedings of the 2004 Winter Simulation Conference: Washington Hilton and Towers, Washington, D.C., U.S.A., December 5-8, 20043*, Association for Computing Machinery, New York, N.Y, Piscataway, N.J, p. 13.

[6] Kritzinger, W., Karner, M., Traar, G., Henjes, J. *et al.*, 2018. Digital Twin in manufacturing: A categorical literature review and classification. IFAC-PapersOnLine *51*, p. 1016.

[7] Zhuang, C., Liu, J., Xiong, H., 2018. Digital twin-based smart production management and control framework for the complex product assembly shop-floor. Int J Adv Manuf Technol *96*, p. 1149.

[8] Glaessgen, E., Stargel, D., 2012. The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles, in *Structures, Structural Dynamics, and Materials and Co-located Conferences: 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference*, p. 1818.

[9] Vachalek, J., Bartalsky, L., Rovny, O., Sismisova, D. *et al.*, 2017. The digital twin of an industrial production line within the industry 4.0 concept, in *Proceedings of the 2017 21st International Conference on Process Control (PC): Hotel Sorea Trigan Baník, Štrbské Pleso, Slovakia, June 6-9, 2017*, IEEE, Piscataway, NJ, p. 258.

[10] Friedli, T., Mundt, A., Thomas, S., 2014. *Strategic Management of Global Manufacturing Networks*. Springer Berlin Heidelberg, Berlin, Heidelberg.

[11] Meixell, M.J., Gargeya, V.B., 2005. Global supply chain design: A literature review and critique. Transportation Research Part E: Logistics and Transportation Review *41*, p. 531.

[12] Klibi, W., Martel, A., Guitouni, A., 2010. The design of robust value-creating supply chain networks: A critical review. European Journal of Operational Research *203*, p. 283.

[13] Chakravarty, A.K., 2005. Global plant capacity and product allocation with pricing decisions. European Journal of Operational Research *165*, p. 157.

[14] Fleischmann, B., Ferber, S., Henrich, P., 2006. Strategic Planning of BMW's Global Production Network. Interfaces *36*, p. 194.

[15] Evans, J.R., 2017. *Business analytics: Methods, models, and decisions*. Pearson, Boston.

[16] Stricker, N., Echsler Minguillon, F., Lanza, G., 2017. Selecting key performance indicators for production with a linear programming approach. International Journal of Production Research *55*, p. 5537.

[17] Mourtzis, D., 2020. Simulation in the design and operation of manufacturing systems: state of the art and new trends. International Journal of Production Research *58*, p. 1927.

[18] Qi, Q., Tao, F., 2018. Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison. IEEE Access *6*, p. 3585.

[19] Pourhejazy, P., Kwon, O., 2016. The New Generation of Operations Research Methods in Supply Chain Optimization: A Review. Sustainability *8*, p. 1033.

[20] Boschert, S., Rosen, R., 2016. Digital Twin—The Simulation Aspect, in *Mechatronic Futures*, Springer International Publishing, Cham, p. 59.

[21] Schuh, A.G., Stich, V., Reuter, C., Blum, M. *et al.*, 2017. Cyber Physical Production Control, in *Industrial Internet of Things*, Springer International Publishing, Cham, p. 519.

[22] Coelho, F., Relvas, S., Barbosa-Póvoa, A.P., 2021. Simulation-based decision support tool for in-house logistics: the basis for a digital twin. Computers & Industrial Engineering *153*, p. 107094.

[23] Negri, E., Fumagalli, L., Macchi, M., 2017. A Review of the Roles of Digital Twin in CPS-based Production Systems. Procedia Manufacturing *11*, p. 939.