Decision Support on the Shop Floor Using Digital Twins

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Architecture and Functional Components for Simulation-Based Assistance

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Abstract. Increased flexibility and improved resilience in production and manufacturing processes are goals that are becoming more and more important in the context of Industry 4.0 and from the experience of the Covid-19 pandemic. At the same time, efficient operation of production must be guaranteed to achieve economic as well as ecological objectives. Intelligent assistance systems follow the idea to support stakeholders of production systems in their decisions and can thus be useful applications for helping to master the various challenges and to meet these goals. In this paper, we describe functional components of these decision support systems: data provision and data extraction, knowledge base, simulation models, model execution and analytics, and application and user interaction. We show the underlying technologies and illustrate why these assistant systems are valuable for several stakeholders.

Keywords: Decision Support, Digital Twin, Shop Floor Management, Simulation

1 Introduction

The optimal operation of automated production systems in the process and manufacturing industry is an ongoing challenge. With the continuous advancements of Industry 4.0, there are more and more opportunities for a more customized and flexible manufacturing of products. Simultaneously, this leads to ever smaller batch sizes and more diverse products with shorter order times and more significant changes in order quantity. In addition to considering quality, time, and cost targets against this backdrop, the flexibility and resilience of the manufacturing processes on the shop floor are therefore inevitably becoming more relevant. Accordingly, the challenges get much more complex with the possibilities of Industry 4.0 and must be solved. Some of these challenges on the shop floor include:

- Virtual sensor: Analyze the behavior and monitor states where no sensor is available.
- Forecasting: Predict future behavior, detect undesirable trends, and prevent them.

- Optimizing of the plant operation: Apply optimization methods to improve plant performance.
- Replay of situations: Analyze situations reversely based on recorded values, e.g., for root cause analysis.
- Offline reconfiguration planning based on the current plant state evaluation for reduced downtime.

In this context, our vision of a Digital Twin can solve such problems and covers the entire lifecycle of production systems and products. However, since such solutions have not yet been sufficiently researched and therefore represent future work, in this paper, we focus on the path to our vision and identify essential functional components for decision support on the shop floor.

2 The Vision of Digital Twin in Production

While so far data-based approaches and artificial intelligence (AI) methods dominate in operation phase, simulation is currently primarily used in design and engineering. A simulation model represents the planned real system and calculates its properties or validates its behavior. With the advancement of simulation technology and the available computing power, these simulation models become more detailed and cover more aspects of the system under development. They thus represent a Digital Twin of the planned system, which leads to an extended understanding of the term Digital Twin [1]. The vision of the Digital Twin refers to a virtual representation and a description of a component, product, system, infrastructure, or process by a set of well-aligned, descriptive, and executable models. It is a semantically linked collection of all relevant digital artifacts, including design and engineering data, operational data, and behavioral descriptions. It exists and evolves along the whole life cycle. Digital Twins integrate the currently available and commonly required information and knowledge and is synchronized with the real twin if it exists.

With the understanding of the seamless reuse of simulation models over all phases of system development and their use for virtual commissioning, simulation models will be applied more and more in the operation and service phases in the future [2]. The combined use of rigorous models from simulation - mainly physics-based models in the manufacturing domain - and AI methods that process operational data will facilitate new, more powerful applications. The decision support for the shop floor and its architecture concept shown in this paper are a step towards this ambitious goal.

3 Related Work

The term Digital Twin has been used for several years now. It is still understood very differently, depending on the perspective and its application, but it is always considered a technological approach with potential, as can be seen in [3]–[5]. One explanation for the different definitions lies in the large variety of physical elements that the Digital

Twin can be linked to. It represents the current status of the real system and can be e.g. used for diagnoses [6] but also in applications to improve the performance of manufacturing systems [7]. Hence, different architectures and frameworks for the implementation of Digital Twins and Digital Twin based applications exist. [8] indicates a Digital Twin to consist of three main building blocks: the physical space, the information processing layer, and the virtual space. The information processing contains essential points with data storage, data processing, and data mapping. In [9], a Digital Twin architecture for a manufacturing cell is presented that consists of six layers. These layers are the physical devices, the local controllers, the local data repositories, the IOT gateway, cloud-based information repositories, and emulation and simulation. OPC UA is used as the communication standard over almost all components. In general, these two works only deal to a small extent with the applications and the functionality and logic that makes the implementation of the application possible, but rather deal with the infrastructure required to implement a Digital Twin. Our work starts at this point and focuses on the functionality and components needed to create applications, more precisely decision support systems, based on the Digital Twin.

[10] presents a survey on decision support systems in manufacturing. The authors discuss simulation-based decision support systems in manufacturing as well as approaches integrating simulation and AI methods. On that basis, a theoretical framework for decision support system development, mainly consisting of a simulation model, a database, an AI component, and a user interface, is presented. [11] discusses digital twin-based machine learning applications in more detail, presenting a framework for implementing them in general. The framework consists of a layer-based architecture for Cyber Physical Systems and Digital Twin, where the Digital Twin mainly serves the purpose of providing data for machine learning algorithms. These works have identified critical components and already address the challenge of linking artificial intelligence methodologies with the model-based approaches of a decision support system. Nevertheless, the approaches miss technologies for integrating production data from heterogeneous sources in knowledge-based models, as well as the flexibility in task completion through hybrid methodologies of AI and simulation. We see the classification in the overall system, including the knowledge representation as improvement to the pure mapping between physical data and virtual operation.

4 Functional Components for Simulation-Based Assistance

4.1 Overview

Decision Support Systems (DSS), in general, are interactive computer-based systems, which utilize data, models, knowledge, and communication technologies to support people who are required to solve complex problems [10], [12]. In our understanding, a decision support system for the shop floor specifies this definition. It bears the integration and connection of heterogeneous production data, simulation models, and AI models, as well as the utilization of reusable and flexible components to address the growing challenges. In this work, we have identified these functional components to build upon to implement decision support systems: data provision and data extraction, knowledge base, simulation models, model execution and analytics, and applications and user interaction. Figure 1 gives an overview of the building blocks and shows a high-level architecture of the Digital Twin that arises from these. In the following paragraphs, we want to discuss these building blocks' functionalities, how they interact and highlight their requirements.

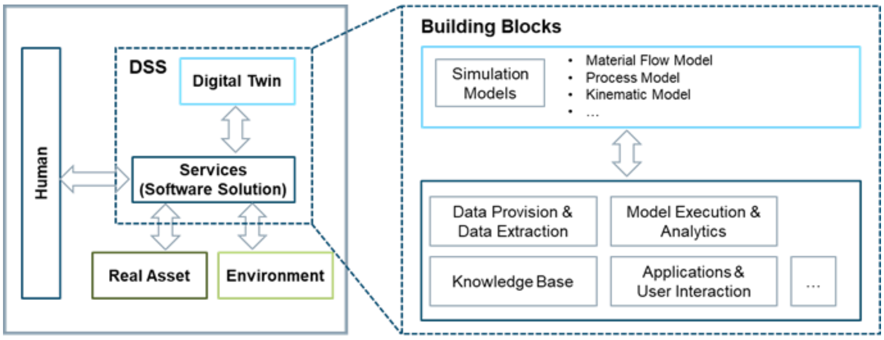

Fig. 1. Building Blocks of Decision Support for the Shop Floor. (extended from [1])

4.2 Data Provision and Data Extraction from heterogeneous IT-Systems

For Industry 4.0 technologies, usually a large amount of data is permanently collected by various sensors, connected machines, systems, and digital models. Due to the evolutionary development of most factories – i.e., new machines and new technologies are permanently integrated into the legacy systems or existing structures of the production system – the data landscape in production systems is very heterogeneous and comes from very different sources, such as MES, ERP, SCADA, machine data and is provided in different structured and unstructured formats e.g., XML, JSON, CSV.

Decision support systems need this data to provide the user with analytical components to make decisions in different situations. However, to feed these analytical components at all, this data must first be extracted from the mentioned systems. For this purpose, already several data-extraction, data-mining [13] and data-cleansing techniques and tools exist that need to be adapted to the production system domain [14], [15]. Nevertheless, data connectors for the different data sources have to be implemented. This is usually a tool or system-specific, or even factory-specific task and often has to be set up and configured anew in each project. To reduce the factory-specific configuration effort, two things need to be simplified:

1. Connectors to existing big data providers in factories such as ERP, MES, etc., based on data communication standards such as OPC-UA or REST, need to be set up.
2. Mapping between the often proprietary data models of existing IT systems and standardized data models needs to be simplified (auto mappers, style sheets, appropriate UI support, data analytics ...).

4.3 Knowledge Base – Data Integration in Semantic Models

It is desirable to relate the just mentioned data and the respective data generators to create a knowledge base, the second building block, to enable and empower analytical components such as machine learning algorithms, simulations, and optimization algorithms. At the same time, this can help to make data extraction more reusable and partially automated [14] and therefore also automate the decision-support algorithms which is quite challenging to implement.

The knowledge base should represent the knowledge in the production line and at the same time be a virtual representation of the production line itself, thus forming an ontology of the production domain. Optimally, each instance within the production, be it a machine, a product, a process, a material, or a worker, can be mapped and related to each other. A more recent technology used for this purpose are knowledge graphs. However, it is not easy to build such large knowledge graphs, especially because of the extreme distribution of individual data [16], [17]. The knowledge graphs must have certain aspects to serve the decision support systems on the shop floor. As described in [18], the use of different layers and applications in decision support requires reusable, standardized, flexible, and extensible means for data exchange between them. This is an essential prerequisite for ensuring that decision support solutions do not have to be rebuilt entirely for each factory but that certain parts can be reused across projects - i.e., following a library or framework approach. In addition, the knowledge graphs must provide structures for two core aspects in particular:

1. Simulation knowledge, which leads to the linkage of simulation components and by that enables the automatic model generation of simulation models.
2. Production knowledge, which brings a deeper understanding of the data and the connections between them.

4.4 Multi-Level Simulation Models

As described above, a knowledge base gives meaning to the data and allows the data to be connected to AI and simulation models. The simulation models, our third functional component, form the basis for the analytic algorithms and represent the current state of production at different levels. That means that depending on the task for decision support, there are different modeling options and levels of details used, e.g., within one production unit or for the entire production stage. In the context of factory simulation, the two main simulation types are material flow simulation and 3D kinematic simulation. In material flow simulation, the logistics inside a production system are modeled e.g., to analyze the dimensioning of the factory and the planning of the production with respect to efficiency, utilization, and in-time delivery, also considering failure situations. 3D-kinematic simulation is used to analyze the interaction within the production cell between machines, like robots, humans, and the product. It is mainly used during the detailed design and commissioning phase [19]. Regardless of the type of simulation, the setup of these models usually requires a huge effort for both the data acquisition as well as the model generation itself [20].

4.5 Model Execution and Analytics for Monitoring, Planning and Scheduling

To deliver value to different stakeholders on the shop floor, the models described above need to be executed, and further analytics need to be added. Besides simulation and optimization, AI is increasingly coming to the fore. The target is to give decision support in a descriptive, predictive, and prescriptive manner.

Descriptive analytics. Data from the current or a previous situation are fed into the simulation model, which is then executed. The simulated plant behavior is further analyzed or evaluated with respect to relevant Key Performance Indicators (KPI), e.g., machine utilization, lead times, blockages, bottlenecks, in-time delivery.

Predictive analytics. Data for upcoming production scenarios are fed into the simulation model, which is then executed. Different alternatives for operational decisions, e.g., production order sequencing and worker assignments, should be examined with respect to the KPIs mentioned above. A systematic experiment management can make use of machine learning approaches reinforcing the most relevant and promising decision alternatives. Uncertainties and risks should be taken into account by also executing particular stochastic deviation and failure scenarios.

Prescriptive analytics. To evaluate upcoming decisions in a systematic way to end up with the best decisions is part of the field of optimization. Production planning and scheduling tasks often lead to NP-hard optimization problems [21]. Therefore, analytical solvers are applicable only in small-size scenarios. For larger problems, meta-heuristics like genetic algorithms, ant algorithms, or neighborhood search are often used instead [22]. It may be a promising approach using machine learning to acquire fast but realistic surrogate models. Any decisions based on heuristics or abstract surrogate models should be further validated by a detailed simulation to end up with a feasible solution (Figure 2).

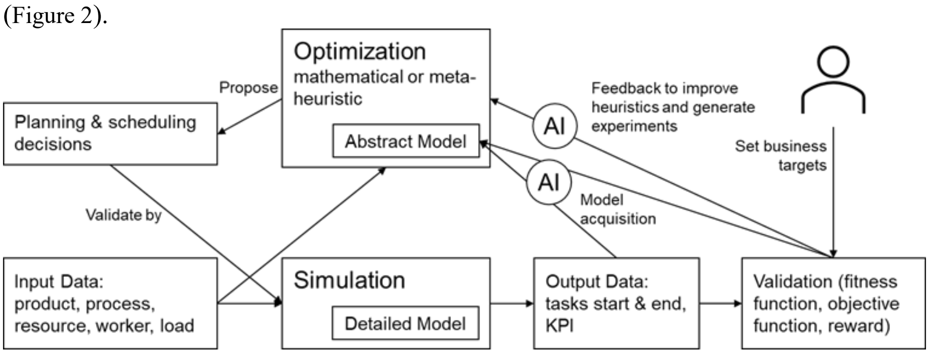

Fig. 2. Hybrid approach for production planning and scheduling

To summarize, the described analytics all require access to field data to synchronize the simulation models with the current situation in the physical world. Hybrid approaches of analytical and data-driven methods can help to manage complexity, but of course, require a lot of data and face challenges in adapting to scenarios not foreseen by previous data.

4.6 User-Specific Application and Interaction

In our last building block, the data calculated by the analytical components is prepared and provided to the various stakeholders. The data must be prepared differently depending on the current situation of the stakeholders in the production. For example, in the case of short-term machine failures, a machine operator needs quick solutions that are understandable. Virtual voice assistants and mobile devices are ideally suited for this purpose. The implementation of the assistant on a personal mobile device answers individual questions and problems so that each person is optimally supported in his or her own work processes. By contrast, planners of larger production sections, for example, may need more information about the problem at hand and the associated solution. For these stakeholders with in-depth technical knowledge, a desktop application with many details to browse through and interact with may be the more appropriate application. Therefore, a solution for the application layer should provide certain flexibility and choices for different representations and information of the data coming from the analytical part within the respective application to serve the different stakeholders depending on their task at hand, their level of knowledge and their authorization.

5 Conclusion

This paper has presented the idea of an operator assistance system for manufacturing and process industries and its main components, namely the data provision and data extraction, the knowledge base, multi-level simulation models, model execution and analytics, and application and user interaction. The functionality of each component and the connection points between them were outlined. Furthermore, the connection to our vision of the Digital Twin as a tool for decision support of the future was shown, where our future work will be dedicated to the implementation. From a scientific point of view, two topics are in the foreground:

1. The conception and implementation of an integrated knowledge base for simulation and production knowledge.
2. Approaches for hybrid models of AI and simulation for decision support on the shop floor.

Furthermore, we will investigate on how to implement more natural interaction mechanisms between production stakeholders and decision support systems. The evaluation of this concept and the individual components within the decision support system is performed using a scheduling problem within a manufacturing environment. The specific tasks concern the validation and optimization of manufacturing schedules, as well as support for make or buy decisions regarding individual parts.

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