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Integrating the Digital Twin of the manufacturing system into a decision support system for improving the order management process

Martin Kunath[a,*], Herwig Winkler[a]

[a]*BTU Cottbus-Senftenberg, Chair of Production and Operations Management, Siemens-Halske-Ring 6, 03046 Cottbus, Germany*

* Corresponding author. Tel.: +49-355-69-4102; fax: +49-355-69-4091. *E-mail address:* martin.kunath@b-tu.de

Abstract

Today´s manufacturing companies need to adapt more than ever to changing customer needs, rising resource costs and increasing uncertainties. A promising way to face these issues is the digitalization of the manufacturing system. Key elements of the digitalization are cyber-physical systems (CPS) and the cyber-physical production system (CPPS). In the last years, the Digital Twin has become a synonym for the cyber-part of CPS and CPPS. In this paper, a conceptual framework and potential applications of a decision support system for the order management process are discussed, that is based on the Digital Twin of the manufacturing system.

Keywords: Digital Twin; Order Management Process; Industry 4.0; Digitalization, Decision Support System

1. Challenges of the order management process

Due to the growing number of varieties per product and the raising customer demand for individualized products, the order management process of manufacturing firms is getting more complex than ever [1]. The consequence is a lack of transparency over the whole process, starting with the customer order and ending with its delivery. Moreover, different process dynamics are leading to additional disturbances in the order management process, e.g. unforeseen machine breakdowns, short-term and irregular orders or changing customer needs and order properties [2]. In this turbulent environment, many manufacturing firms are trying to keep the profitability and efficiency on a constant level using forecasts and statistical methods to anticipate future demand [3] or the probability of a machine breakdown. They are investing in the optimization of the production process, to improve the capacity utilization [4], or in further storage capacities [5], to face unpredicted demands. However, when any disturbance occurs, the problem is solved locally by ad-hoc solutions, without considering the impact on other steps of the order management process.

For the control of the order management process and the production process different information systems are used, e.g. enterprise resource planning (ERP) systems and manufacturing execution systems (MES). Traditional tasks of production planning and control are the planning of the production program, the material requirements planning, scheduling and job sequencing under consideration of required and available production capacities. Each planning stage produces data and information for another planning stage. Changes in one plan, as a result of unforeseen job-related or resource-related dynamics, will automatically lead to necessary changes in another plan [4].

Nomenclature

CPS	cyber-physical systems
CPPS	cyber-physical production system
ERP	enterprise resource planning
MES	manufacturing execution system
NASA	National Aeronautics and Space Administration
PDM	product data management
PPC	production planning and control

The main challenge of replanning and rescheduling is to find suitable solutions, which support almost all company goals and improve the overall performance of the production system, instead of achieving a local optimum. The quality of each solution depends on the experience of the decision maker and the available information. High experienced employees can anticipate the consequences of their decisions easier for previous and following process steps than employees with low experience. Nevertheless, the accuracy of manual calculation and predication of the probability of an event is very low, regardless of the experience level. To reduce the own risk, solutions are preferred, that will have at least a beneficial effect for the decision maker [6].

In the worst case, a decision will lead to further unpredicted disturbances. Although there are basically better solutions, which support the overall performance of the production system, their benefit for the company is not recognized, because of missing information and low transparency. Moreover, better solutions are neglected in fear of local deterioration of the performance or for individual reasons.

A system for the decision support is needed to predict the advantages and disadvantages of different solutions and give recommendations for the best solution with respect to the individual and changing company goals. Moreover, such a system could automatically return the optimal solution to the manufacturing system, if allowed by the user. The basis of such a system will be a detailed real-time representation of the whole production system, henceforth referred to as the Digital Twin of the manufacturing system. Through simulating different scenarios in a model, representing the current state of the system, solutions will be found, which support local and global goals. The consequences of each decision will be transparent, without creating disturbances in the real system. In this paper, a concept of integrating the Digital Twin of the manufacturing system in a decision support system and its role for supporting the order management process are presented.

The paper is structured as follows. In section 2, the main concept of the Digital Twin in the context of simulation is explained. Next, an adapted concept of the Digital Twin of the manufacturing system and its integration into a decision support system are described in section 3. Section 4 focuses on the role of the decision support system for the order management process. Finally, a discussion is presented in section 5.

2. The concept of the Digital Twin in the context of simulation

The term Digital Twin has been published first by the National Aeronautics and Space Administration (NASA) in 2010. They define the Digital Twin as an ultra-realistic, high scaling simulation, which uses the best available physical models, sensor data and historical data for mirroring one or more real systems. The relevant data is collected throughout the whole lifecycle of the system [7]. The main dimensions are time and level of detail. Relevant data will be acquired continuously and transferred in real-time to the Digital Twin of the system. The Twin itself can be used in different levels of detail. In addition to the actual state of the system, a historical state or alternative states can be used for an analysis [8, 9].

From the publication of the NASA, three main functions of the Digital Twin can be summed up [7]:

- Prediction – execution of studies ahead of the system run
- Safety – monitoring and control of the system state in terms of a continuous prediction during the system run
- Diagnosis – analysis of unpredicted disturbances during the system run

As concluded by Negri et al. (2017), the literature provides two main views on the Digital Twin in the context of simulation. On the one hand, they define the Digital Twin as a kind of model, different types of simulations can be derived from. On the other hand, the Digital Twin itself is often defined as a simulation [10]. Simultaneously, authors supporting the first view are defining the Digital Twin as a combination of different models, data and information [9, 11, 12, 13].

For Boschert and Rosen (2016), the Digital Twin is the next level of simulation. Mainly used for single or multiple analysis, simulation will become the main tool for decision support, once the Digital Twin is fully integrated, as shown in Fig. 1. Instead of comparing the Digital Twin with a single simulation model, they define it as an abstract concept. The Digital Twin will have its own architecture that connects engineering data, operational data and behavior descriptions through different simulation models. These models will be manually generated and later updated by a model management system. Moreover, the model management system will choose the right simulation model for specific problems [9].

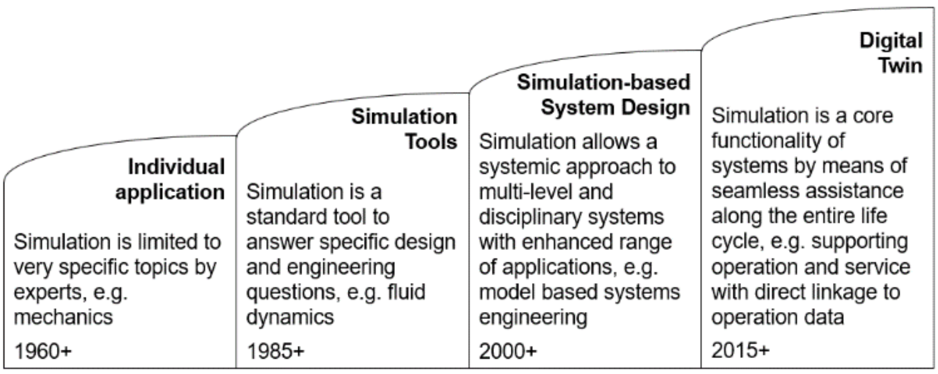

Fig. 1: The Digital Twin as the next level of simulation [9]

Schluse and Rossmann (2016) are focusing on using Digital Twins for experimental simulations in virtual testbeds. For them, the Digital Twin is the virtual representation of a physical subject or object based on models of its data, functionality and communication interfaces. A simulation database is introduced that integrates different data sources, simulation systems as well as visualizations and helps to perform any type of simulation. The sum of different simulation models and systems realizes the Digital Twin [11]. Schroeder et al. (2016) are defining the Digital Twin as a model, consisting of data, conducted over the whole lifecycle of a product, and different kind of models, e.g. system models, functional models or 3D models. They are referencing on the method of Computer Aided Engineering Exchange that helps to describe physical objects as data objects and exchange data between different applications [12]. Stark et al (2017) are mainly focusing on production systems. For them, the Digital Twin is the intelligent linkage of the Digital Master, representing a universal simulation model of the physical system, and the Digital Shadow, i.e. all operational data. The linkage should be done by algorithms, simulation models and other relations [13].

Negri et al. (2017) are concluding that the Digital Twin is the digital representation of a physical object. The digital representation is based on a semantic data model that enables to perform simulations for different purposes. While these simulations can help to predict the future behavior of the object, the semantic data model helps to continuously update the virtual representation with real-time data [10].

In conclusion, we define the Digital Twin of a physical object as the sum of all logically related data, i.e. engineering data and operational data, represented by a semantic data model. While engineering data is generated once and updated when necessary, e.g. 3D models, specific simulation models or material specifications, operational data is gathered and processed in real-time. Following this definition, the Digital Twin can represent historical and real-time states of the physical object. Using specific applications, a real-time visualization of the physical object can be generated, combining a 3D model with real-time data. Furthermore, different simulations can be performed, using existing simulation models or by generating new models that will become part of the Digital Twin.

To realize the Digital Twin as a real-time representation, the physical object needs to be digitalized, combining engineering data and operational data. In the context of a manufacturing environment, sensors, communication systems and embedded systems must be integrated in machines and further elements of the manufacturing system. The gathered data needs to be transferred via a network from the physical object to its digital representation in the information world. Adding actuators to the physical object, computed instructions can be retransferred from the Digital Twin to the physical world. This concept of combining physical processes with computation is already know under the term cyber-physical system (CPS) [14]. Following the 5C architecture for implementing CPS, the Digital Twin can be seen as the cyber-part of CPS [15]. As different CPS interlink in a manufacturing environment, the production system will become a cyber-physical production system (CPPS) [16].

3. The Digital Twin of the manufacturing system as the basis of a decision support system

3.1. Subsystems and elements of the manufacturing system

The manufacturing system can be separated into the manufacturing equipment system, the material flow system, the value stream system, the operating materials system, the human resource system and the information system. The manufacturing equipment system, consisting of machines and tools, represents the core of the value creation process. One of the main tasks is the transformation of raw material into products. Raw material, workpieces, products and residual materials are value objects and therefore elements of the value stream system. These value objects are handled and stored by the material flow system. The main task of the material flow system is the supply of the manufacturing equipment system with needed materials, under consideration of schedules and sequences, the disposal of waste and the storage and transportation of products. To keep the manufacturing equipment system and the material flow system running, different elements of the operating materials system are needed, e.g. energy, compressed air, lubricants and cooling materials. The human workforce is part of the human resource system and supports or executes tasks of the manufacturing equipment system and material flow system. All tasks of the introduced systems are supported by the information system. The information system conveys data and information in a physical and digital way between all systems. Simultaneously, data and information of these systems are exchanged with production planning and control (PPC) systems, e.g. MES or ERP systems [4].

3.2. The Digital Twin of the manufacturing system

We define the Digital Twin of the manufacturing system as a data-oriented representation of all elements of the manufacturing equipment system, the material flow system, the value stream system, the operating materials system and the human resource system in the information world, which are linked to their physical elements by the information system as depicted in Fig. 2. These elements are connected to each other and to the information system by sensors, actuators and communication systems, to support the concept of a CPPS. The main purpose of the Digital Twin of the manufacturing system is to facilitate the decision-making process and to enable decision automation through simulation.

Following the concept of interlinking CPS to create a CPPS [16], the Digital Twin of the manufacturing system can be seen as an intelligent linkage of the Digital Twins of elements of the manufacturing system. Therefore, the Digital Twin of the manufacturing system will have its own semantic data model that describes the relations of all these elements. In addition, the Twin contains separate engineering data, e.g. 2D or 3D layouts and simulation models. As explained in section 2, a 3D model can be combined with real-time data in a specific application to generate a real-time visualization of the manufacturing system. Furthermore, simulation models can use real-time data to perform simulation experiments

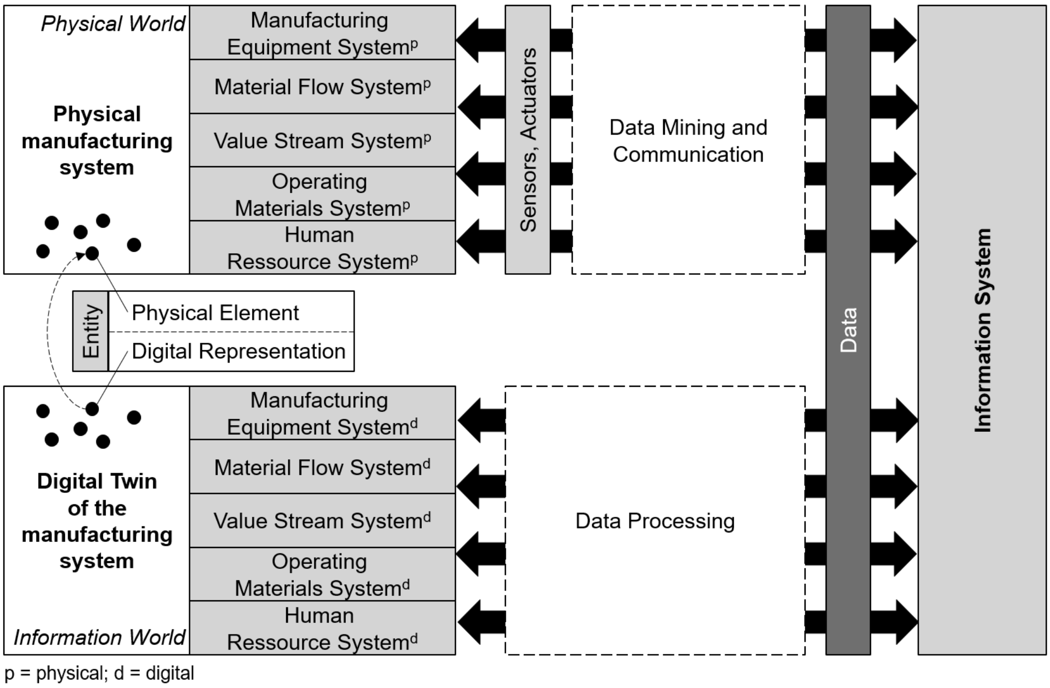

Fig. 2: Data-oriented connection of the manufacturing system and its Digital Twin

considering the actual state of the system. If a decision is needed that cannot be supported by the existing models, new models have to be created.

3.3. A conceptual framework of the decision support system for the order management process

The Digital Twin of the manufacturing system is not able to support the order management process solely, as it is not containing information concerning orders, products, schedules, company specific priorities and further data that is necessary to control the order management process. Therefore, the Twin must be integrated into a suitable decision support system.

Existing PPC systems, e.g. ERP systems and MES, are still necessary in a company and will not be replaced by such a decision support system. The problem is, each of these PPC systems supports different tasks of the order management process [18]. The decision support system will integrate all PPC systems as well as product-oriented systems, e.g. product data management (PDM) systems, for an improved way of decision-making over the whole order management process.

For giving recommendations in a specific decision situation a simulation model of the manufacturing system is still needed. As defined in section 3.2, the Digital Twin of the manufacturing system integrates the Digital Twins of its elements and has its own models. Following the concepts of Boschert and Rosen (2016) and Schluse and Rossmann (2016), a suitable simulation model could be chosen from a simulation database and combined with real-time data [9, 11]. Furthermore, a new simulation model could be automatically generated using semantic data models as well as engineering data and operational data from each element of the manufacturing system. In the decision support system, an automatic model generator will be responsible for the generation and the management of the simulation models.

In order to support the control of the order management process, decisions have to be made in real-time. The real-time requirement implies, that decisions are made fast enough, without causing disruptions in the real system. The specific time varies for each decision situation [19]. As irrelevant data will cause long computation times, the simulation model should only consist of relevant data, which is needed for the decision situation, e.g. information concerning all waiting and released orders, machine states, geo locations of workers and inventory stocks. Hence, the simulation model will be a near-real-time representation of the manufacturing system [20], [21]. Furthermore, intelligent algorithms are needed that help to execute the simulation and to evaluate the simulation outcome in consideration of the company's target system.

Following requirements can be summarized for the decision support system:

- Integration of all relevant data of the order management process for real-time decision support
- Connection to the existing information system of a company and expansion capability
- Digitalization, unique identification and interlinkage of all elements of the manufacturing system
- Integration of the Digital Twin of the manufacturing system as a real-time representation of all elements of the manufacturing system
- Automatic simulation model generation and update for specific decision situations
- Application of self-learning planning and control algorithms

The concept of integrating the Digital Twin of the manufacturing system into the decision support system is shown in Fig. 3. In a logical way, the information world contains the Digital Twin of the physical manufacturing

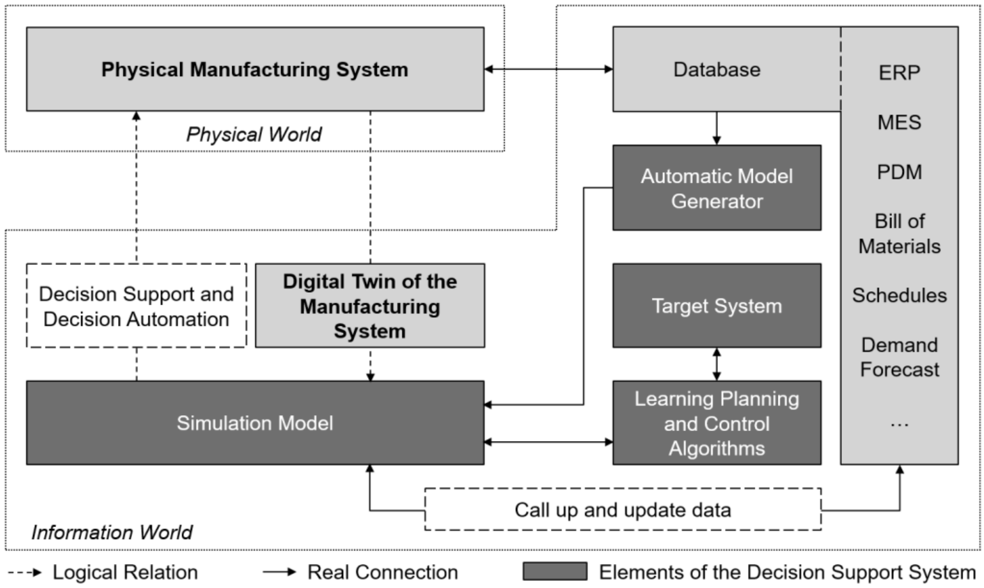

Fig. 3: Integration of the Digital Twin of the manufacturing system into a decision support system for the order management process

system. The Twin is used as a simulation model for decision support and automation. In practice, the elements of the physical manufacturing system are connected to information systems and databases. The automatic model generator will choose and update a proper simulation model or generate a new one, using data and information from all these databases and information systems. During the simulation, the learning planning and control algorithms will search for the best solution for the decision problem considering the company´s target system. When a solution is found, the solution and maybe some alternative solutions are presented to a decision maker. Furthermore the best solution could automatically be returned to a specific information system or database and if necessary forwarded to the manufacturing system.

4. Application possibilities of the decision support system

4.1. Dynamic, simulation-based scheduling

In many companies, priority dispatching rules are used, to simplify the scheduling process. These rules are supporting one or more company goals, e.g. to minimize the makespan, the work in progress or the production costs [22]. One mayor challenge is, none of the existing rules performs well enough in complex manufacturing systems [23, 24]. An improvement can be achieved by a simulation-based scheduling system. An appropriate decision support system can schedule the orders under consideration of the current system state and propose schedules improving the overall performance of the company. Instead of using one single priority dispatching rule, simulation runs with different rules are compared [25, 26, 27] or intelligent search algorithms are used [28, 29, 30].

When such a system is connected to the MES, the best schedule can be transferred automatically to the manufacturing system. The main requirement is the complete implementation of the Digital Twin of the manufacturing system. From the Digital Twin, information regarding the material availability, the resource availability, the requested delivery dates, the localization of a worker or the localization of a transport system can be integrated into the scheduling process [30]. Companies with a low level of automation will have to implement suitable technologies for the communication with workers. As the dissemination in private live raises, smartphones and tablets with specific apps are promising systems for that purpose [31].

4.2. Dynamic calculation of delivery dates and dynamic pricing as a part of the offering process

In a make-to-order production the order gets evaluated, a delivery date is set and the final price is calculated before the offer is prepared. Especially the calculation of the delivery date is associated with uncertainties. In most cases, only vague information is available. Companies must adapt the offer to comparable orders and trust in the experience of their staff. The consequence of using estimated values is often, that delivery dates cannot be met or only with additional costs [4].

When the concept of the Digital Twin is fully implemented in a company, the Digital Twin of the product will be available from the design phase, over the engineering phase, until the after-sales phase. The Digital Twin evolves simultaneously with the real product and provides simulation models, material requirements and construction characteristics [9]. This information can be usefully integrated into the offer preparation. Instead of using estimated values, the production of the product and the whole order processing can be simulated using the Digital Twin of the product and the manufacturing system. Processing times and throughput times can be calculated and the earliest due date can be set, considering the current state and order backlog of the manufacturing system.

In the proposed concept, the impact on the target system of the company is not appropriately considered. If an order is urgent, i.e. the requested delivery date is close to the earliest due date, priorities for this order must be set for each machine, to reduce waiting time. This can lead to additional set-up time or even overtime, if capacity limits are reached. The additional costs that arose due to the individual prioritization can be calculated through simulation. During pricing, the material costs, the production costs and the additional costs, which represent the unavoidable performance decreasing for the individual prioritization, can be proportional summed up for calculating the final price. For logical reasons, the offering system should be integrated in an online tool that is connected to the decision support system. The customer will be able to define the delivery date in the way of an online flight reservation. Delivery dates that raise the performance of the company will result in lower prices and vice versa.

4.3. Dynamic calculation of delivery dates and dynamic pricing as a part of the order processing

If the customer is requesting any changes during the order processing, e.g. an earlier delivery date, the decision support system can recalculate the price considering the impact on the performance of the manufacturing system. In addition, the system can find alternative schedules through simulation that improve machine utilization, but will result in a shift of due dates. If an order is completed ahead of the requested delivery date, the products must be stored. The consequences are higher storage costs. If an order is completed after the requested delivery date, the company often must give a discount or the customer satisfactory will decrease. In the first scenario, a discount can be offered, that is comparable to the imminent storage costs, if the customer will accept an early delivery. In the second scenario, a partial discount for the late delivery can be offered, that is comparable to the raising performance of the manufacturing system. Instead of accepting the negative consequences of requested changes or rejecting possible opportunities of rescheduling, the decision support system can help to reveal advantages for the company and the customer.

4.4. Dynamic administration of supply processes

Beside the planning and control of production orders, the order management process also includes subcontracting and the management of supply orders. For improving the supply chain management, it is necessary that parts of the Digital Twin of the manufacturing system and relevant information are available for each partner in the supply chain. Any disturbance in the production process of the supplier could initiate the rescheduling process in the own company. In case of a larger production downtime, the selection of an alternative supplier could be automatically done. If each company is represented by its Digital Twin on a Digital Manufacturing Market, the required production technologies and product characteristics can be compared to the manufacturing system of the available suppliers [32].

When a suitable supplier has been found, the current capacity utilization, the ability to supply and the delivery quality can be assessed. The described scenario exceeds the functions of the proposed decision support system. In fact, the decision support system should be connected to the Digital Manufacturing Market, to provide and process necessary information.

5. Conclusion

The raising complexity of the order management process decreases the ability of companies to remain flexible and profitable. A promising way to face these challenges, is the integration of the Digital Twin of the manufacturing system into a decision support system for improving the order management process. One major element of the decision support system is an automatic model generator that builds simulation models, using information from the Digital Twin of the manufacturing system. The Digital Twin itself is defined as the sum of all available data, i.e. engineering data and operational data, of all elements of the manufacturing system that reflect the historical and actual state of the system in real-time. The manufacturing system is subdivided into the manufacturing equipment system, the material flow system, the value stream system, the operating materials system and the human resource system. Each element of each subsystem of the manufacturing system is represented in the information world and linked to its physical element by the information system. Using intelligent and self-learning search algorithms, the decision support system can improve the overall performance of a company and the whole supply chain.

The realization of the Digital Twin of the manufacturing system is associated with a lot of challenges. Until now, only a few companies are using technologies for the identification and localization of products, machines and especially workers. Reasons are the supposed high costs and unsolved questions regarding data security. Moreover, the data quality of motion data in production is quite low and can be rarely used for a simulation-based analysis. Especially small and medium sized companies are still performing manual data acquisition. Therefore, the real-time requirement cannot be fulfilled [33]. The concept of an automatic model generator has been already explained in some papers [20, 34], but is not realized in common factory planning software systems. Finally, when the Digital Twin of the manufacturing system is realized in a company, missing standardization will be a major challenge for a cross-company utilization [35].

As the shown benefit of realizing and implementing the Digital Twin of the manufacturing system in a decision support system is quite high, companies should be motivated to invest in suitable technologies. First partial examples are already implemented in different companies [31]. Instead of realizing the Digital Twin of the whole manufacturing system, the focus is set on specific machines and products. Therefore, researchers are already searching for feasible solutions to realize the Digital Twin of the manufacturing system in every company [35].

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