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Concept of a plug-and-play, Machine Learning Digital Twin of the production resource for Detailed Capacity Planning and Scheduling

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Abstract

Due to the progress of Digital Production and the Industrial Internet of Things, continuous shop floor data is available with high coverage, accuracy, and in high detail for Production Planning and Control software. Detailed Capacity Planning and Scheduling (DCPS) can benefit by applying the Digital Twin concept and Machine Learning for an accurate and automated virtual representation of the production resource. However, the effort and difficulty required for data connection, data preparation, and modelling are high. Connection standards enable interoperability and plug-and-play software, and constitute an opportunity to reduce the effort and difficulty. This article compiles requirements regarding the virtual representation of the production resource for DCPS. It then proposes the concept of a plug-and-play, Machine Learning Digital Twin to meet these requirements. The elements of the according Digital Twin software are described, and the need for future research is identified.

Keywords: Production Planning and Control, Digital Twin, Machine Learning, interoperability

1. Introduction

Detailed capacity planning and scheduling (DCPS) is a subtask of Production Planning and Control (PPC), at which production operations are allocated to production resources, capacity demand and availability are determined and aligned, and exact operation dates are scheduled [1, 2]. By this, DCPS improves the on-time delivery rate and the

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utilisation of production resources. DCPS also increases the probability of actual shop floor adherence to the production plan. Buffer times and subsequent work-in-progress inventory can therefore be kept at a low level, and suboptimal production plans resulting from replanning are avoided [1]. In sum, DCPS increases the logistical performance and efficiency of production systems. These goals are strategically important for production organisations [3]. The deployment of PPC software which include DCPS functionalities, such as Manufacturing Execution Systems (MES) and Advanced Planning and Scheduling systems (APS), is widespread [4].

The primary production resources that operations are allocated to in DCPS are work units such as machines or assembly stations [2, 5]. They are virtually represented in PPC software, where models map the resource properties which are relevant for planning and predict capacity parameters, such as production time and technical efficiency. The effectiveness of DCPS strongly depends on predicted capacity parameters corresponding with actual shop floor data, and knowledge-based estimates often do not provide sufficient accuracy [1, 6]. Production organisations see the improvement of the accuracy of planning parameters as a main measure to improve their on-time delivery rate [7].

With the progress of Digital Production and the Industrial Internet of Things, shop floor data acquisition and network access of data acquisition systems have increased. Continuous shop floor data is available with high coverage, accuracy, and in high detail to be connected to and used in software [8]. PPC is seen as a main beneficiary of the improved data availability [9]. Following the idea of Industry 4.0, shop floor data can be deployed to apply the Digital Twin concept and data-driven modelling through Machine Learning, and thereby establish an accurate and automated virtual representation of the production resource. Digital Twins in production entail a synchronisation of the virtual representation and the real-world object [10, 11]. They typically use a data connection to update states and adapt properties that are required for decision support based on continuous shop floor data, e.g. through data-driven modelling [12, 13]. However, the high effort and difficulty required for data connection, data preparation, and modelling represent burdens for applying the Digital Twin concept and Machine Learning [14]. Approaches described in scientific literature do not yet address a corresponding solution for DCPS. At the same time, the development of industrial connection standards has advanced, and their adoption has increased [15]. They enable interoperability and plug-and-play software, and constitute an opportunity to address the described challenge [14].

This article proposes the concept of a plug-and-play, Machine Learning Digital Twin for the virtual representation of the production resource for DCPS. Section 2 discusses related work. Section 3 then presents application scenarios that illustrate the benefit of a data-driven modelled Digital Twin. Section 4 compiles the requirements regarding the virtual representation of the production resource for DCPS that are stated in scientific literature, which are then verified by empiric case studies. Based on the requirements, section 5 presents and describes the solution concept. The requirements and the concept are evaluated by expert interviews. Section 6 discusses the concept. In conclusion, section 7 identifies the need for future research to develop a Digital Twin software in accordance with the concept.

2. Related work

Several approaches are described in scientific literature regarding the virtual representation of the production resource in PPC software and the modelling of capacity parameters. The data-driven approaches of [6, 16–18] deploy shop floor data for an accurate modelling of capacity parameters. Capacity parameters are modelled as expected values, distribution functions, or univariate functions that describe a known correlation to an influencing factor such as the product group. Multiple and dynamic influencing factors like production conditions are not considered. [19–21] use Machine Learning to model multivariate functions, where correlations to influencing factors are unknown. The adaptive approaches of [22–25] emphasise the change of resource properties over time. They use a data connection to adapt models of capacity parameters based on continuous shop floor data and can be regarded as Digital Twins. In the approach of [26], the need to remodel capacity parameters is identified by deviations from shop floor data. The modelling of capacity parameters is then carried out knowledge-based, assuming it to be more accurate than data-driven modelling. Approaches that are explicitly described as Digital Twins in the context of PPC use a data connection to the production resource to update the state or to execute functionalities, but not to map properties [27, 28]. [29, 30] describe the benefit and requirements of applying the Digital Twin concept to represent production resources and the production system in PPC software. Capacity parameters of production resources are stated as required properties to be mapped by a Digital Twin for PPC by [31]. [32–34] define methods and building elements to develop Digital Twins for PPC.

The presented data-driven and adaptive approaches are effective to accurately model capacity parameters. However, the high effort and difficulty required for data preparation and modelling, as well as for the implementation of an automated software, which uses a data connection and Machine Learning algorithms, are stated. The approaches do not yet address a corresponding solution and plug-and-play software.

3. Application scenarios

Current approaches of production organisations regarding the virtual representation of production resources for DCPS often reveal shortcomings. Three real-world examples from different industries that are described in the following illustrate these shortcomings, as well as benefits of a Digital Twin with data-driven modelling of capacity parameters. They represent potential application scenarios.

Application scenario 1: An organisation that produces strip steel carries out demand planning and rough scheduling in Enterprise Resource Planning (ERP) software, and conducts DCPS for some of the production lines in an APS. While delay times are modelled data-driven, the modelling of production times is knowledge-based or default values based on the production technology, like feed. The approach proves to be inaccurate, the default values reflecting ideal values that do not include unrecorded short delay times. As a result, on-time delivery rates do not meet expectations and work-in-progress inventory is high, as planning inaccuracies are compensated by buffer times.

Application scenario 2: An organisation that produces automotives uses Discrete Event Simulation (DES) to carry out capacity planning and ensure that the final assembly lines and their material supply systems meet the capacity demand of the production plan. Modelling of capacity parameters is knowledge-based, or based on supplier information and technical data sheets. These parameters often prove to be inaccurate. An alternative modelling approach is data-driven based on shop floor data from the corresponding or a similar assembly line. The provided data is extensive and heterogeneous. The effort required for data provision, data preparation, and modelling often takes up much or exceeds the available time and resources to carry out DES-based capacity planning, and is re-conducted for each capacity planning initiative.

Application scenario 3: An organisation that produces semiconductors optimises their DCPS procedure to improve on-time delivery rate and resource utilisation by applying Reinforcement Learning. A virtual agent is trained based on a DES model, resulting in an optimised DCPS procedure. The procedure is then transferred to the real-world DCPS. A challenge when applying Reinforcement Learning is the simulation-to-reality gap, which refers to the deviation between the simulation model and the actual production system, which is also caused by inaccurate and non-adaptive mapping of properties [35].

4. Requirements

This section compiles requirements regarding the virtual representation of the production resource for DCPS that are stated in the reviewed scientific literature. The requirements are verified and amended based on two empiric case studies. Case study 1 examines the bottleneck resource group within a production line of an organisation that produces strip steel. Shop floor data from the production resources is recorded based on manual machine operator entries, including production time, setup time, delay time, good quantity, and scrap and rework quantity. It is compared to capacity parameters that were predicted for planning in the APS, and a DES is used to analyse the effects of deviations. The DES model is deployed by the production organisation for factory planning and was validated by metrics comparing it to the real-world production system, as well as by expert analysis. Case study 2 examines an additive manufacturing workshop that is operated in a scientific institute. Shop floor data is recorded based on time series data from sensors and event data created by the machine control. By that, production times and delay times are recorded in a MES, as well as production parameters and production conditions. The technical efficiency of one machine is analysed along with correlations to production parameters and production conditions. The requirements were evaluated by four questionnaire-based interviews with PPC experts from scientific institutes and production organisations, and subsequently adjusted. The requirements are grouped by the main aspects of integration in the procedure of DCPS (section 4.1), sufficiency (section 4.2), accuracy (section 4.3), and effort and difficulty to create and maintain (section 4.4). Section 4.5 provides a summary of the requirements with a reference to their description in the previous sections.

4.1. Integration in the procedure of DCPS (R1)

A systematic DCPS is usually carried out with the support of PPC software [1, 2]. APS is a dedicated software for DCPS, while MES typically entail DCPS functionalities [5]. ERP software generally support demand planning and rough scheduling, additional functionalities for DCPS are sometimes included. DES is also be used to support DCPS. The virtual representation of the production resource must provide capacity parameters to these types of PPC software (R1.1). Production organisations potentially use predicted capacity parameters of a specific production resource in several software also for other capacity planning tasks, like factory planning or demand planning and rough scheduling. The predicted capacity parameters must then correspond for consistent and effective planning (R1.2). Relevant influencing factors may only be included in the modelling of capacity parameters when they are available for planning in the deployed PPC software or the virtual representation (R1.3).

4.2. Sufficiency (R2)

DCPS predicts the capacity demand of production operations, capacity availability of production resources, and the dates of operations [2]. Capacity parameters that are relevant for this must be provided by the virtual representation of the production resource (R2.1). DCPS must be executable when required, a low accuracy of the predicted capacity parameters is preferred over capacity parameters not being provided at all. That is the case when relevant influencing factors cannot be determined at the time of planning or no applicable shop floor data has been recorded (R2.2, R3.3). A resource schedule must provide the resource's availability, excluding already allocated production and maintenance operations, and non-operation times. For the allocation of production operations, resource capabilities and production costs must be provided by the virtual representation, as well as restrictions, e.g. lot sizes or sequence rules (R2.4) [31].

4.3. Accuracy (R3)

The deviation of capacity parameters predicted for planning from actual shop floor data must be low for effective DCPS (R3.1) [6, 17]. In case study 1, the mean deviation of the predicted production time per unit from the recorded shop floor data is -18% (Fig. 1). The mean absolute deviation is 31%. An evaluation through DES shows that a deviation of -18% of the predicted production time leads to a 2,6% reduction of the on-schedule delivery rate for the production line, when not compensated by buffer times and subsequent work-in-progress inventory. The shop floor data in case study 1 show a high variance, as shown in fig. 1. More than 10% of the recorded production time per unit fall 47% or more below the mean, another 10% exceed the mean by 65% or more.

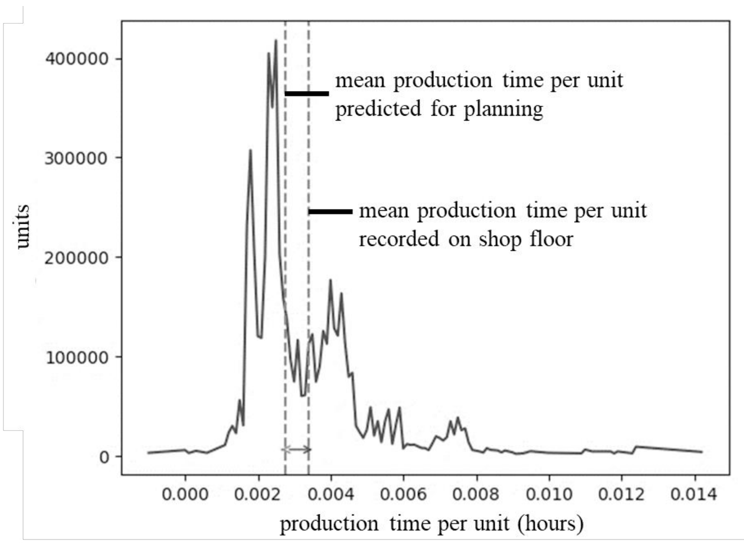

Fig. 1. Recorded shop floor data of the bottleneck resource group in case study 1 (own figure).

Some approaches described in scientific literature address the variance by modelling capacity parameters as distribution functions and determining a robust DCPS result through simulation experiments [16, 17]. The variance of actual capacity parameters decreases when linked to relevant influencing factors, and the accuracy of capacity parameters predicted for planning must be improved by considering multiple influencing factors (R3.2). That is addressed in approaches that model capacity parameters as functions to correlating influencing factors [20, 21]. In case study 2, the inert gas filter differential pressure, which is an indicator of contamination that leads to delay times, shows a linear correlation to the technical efficiency with a coefficient of -0.69, as shown in table 1.

Table 1. Correlation coefficients of several production parameters and conditions with technical efficiency in case study 2.

Production parameter/condition	Correlation coefficient with technical efficiency
Inert gas flow velocity	0.22
Inert gas filter differential pressure	-0.69
Temperature in build envelope	-0.04
Pressure in build envelope	0.13

The accuracy of the modelled capacity parameters must be improved by adapting to their change over time which is not reflected by functions to correlating influencing factors (R3.3). That is addressed in adaptive approaches for modelling capacity parameters [22, 23]. Such changes are caused by new product properties, changes in production parameters, or changing production conditions. In case study 2, the simple moving average of the technical efficiency gradually increases by about 4 percentage points over the course of 4 months (fig. 2).

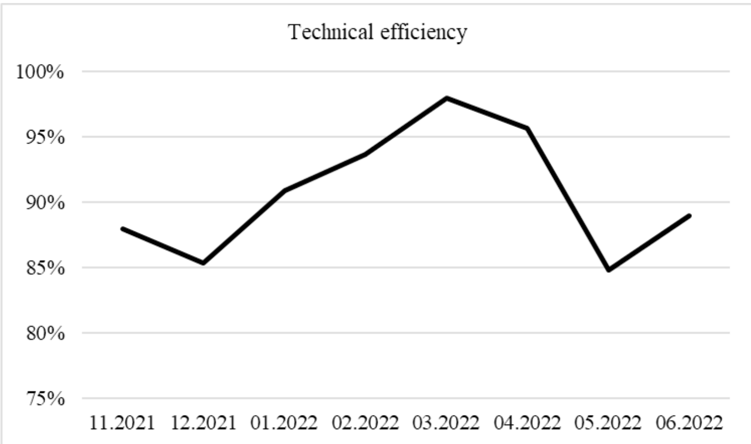

Fig. 2. Simple moving average of technical efficiency in case study 2 (own figure).

4.4. *Effort and difficulty to create and maintain (R4)*

The high effort and difficulty are main challenges for creating and maintaining virtual representations of production resources with the required accuracy [16, 20, 25]. The modelling requires expert knowledge of the production system and potentially data-driven modelling competencies, which are scarce [14]. High personnel time and competencies are also needed to provide and prepare shop floor data to support the modelling of capacity parameters. Shop floor data is often unstructured and provided in various types of communication protocols and data formats by heterogeneous data acquisition systems. Ultimately, the adaption of models of capacity parameters and provision to PPC software adds to the effort needed. To avoid that capacity parameters are not being modelled in the required accuracy, the effort and difficulty for data provision, data preparation, and modelling must be low (R4.1, R4.2).

4.5. Summary

The compiled requirements are listed in table 2. The solution concept proposed in Section 5 references these requirements.

Table 2. Requirements for the virtual representation of the production resource for DCPS.

Requirement	Description
R1	The virtual representation must be integrated in the procedure of DCPS.
R1.1	Capacity parameters must be usable in PPC software, e.g. ERP, MES, APS, or DES.
R1.2	Capacity parameters must be provided to all deployed capacity planning software.
R1.3	Functions for capacity parameters may only include correlating influencing factors that are available in the deployed PPC software or the virtual representation.
R2	The virtual representation must be sufficient for DCPS.
R2.1	Models of capacity parameters must enable the prediction of capacity demand, capacity availability, and dates of production operations.
R2.2	Capacity parameters must be predicted also when influencing factors cannot be determined at the time of planning.
R2.3	Capacity parameters must be predicted for planning also when no applicable shop floor data has previously been recorded.
R2.4	A resource schedule, resource capabilities, restrictions, and production costs must be provided for the allocation of production operations.
R3	The virtual representation must be accurate.
R3.1	The deviation of predicted capacity parameters for planning from actual shop floor data must be low.
R3.2	Correlations to influencing factors must be mapped in functions for capacity parameters.
R3.3	Capacity parameters must be modelled continuously.
R4	The effort and difficulty to create and maintain the virtual representation must be low.
R4.1	The personnel time spent and the competencies required for modelling capacity parameters must be low.
R4.2	The personnel time spent and the competencies required for providing and preparing data must be low.

5. Concept

Based on the compiled requirements, this section proposes a solution concept to meet these requirements. It is referred to as a plug-and-play, Machine Learning Digital Twin of the production resource for DCPS. The Digital Twin adapts properties of the production resource based on continuous shop floor data. The Digital Twin software is automated through a data connection, a data transformation algorithm, and a Machine Learning algorithm. Additionally, it is plug-and-play capable by supporting connection standards and including a uniform, generally applicable data model and Machine Learning algorithm. The data model consists of a resource-agnostic data structure and standard capacity parameters. The Digital Twin software is accompanied by a method to support the manual steps of data preparation. The solution concept was evaluated and adjusted based on four semi-structured, questionnaire-based expert interviews along with the requirements.

An overview of the proposed Digital Twin is outlined in fig. 3. It is based on the building elements of Digital Twins for PPC of [33], as well as the Cross-Industry Standard Process for Data Mining, a standard methodology for data-driven modelling [36]. The continuous shop floor data from the data acquisition system is transformed by the algorithm and recorded in the resource-agnostic data structure. The Machine Learning algorithm continuously models standard capacity parameters for PPC software that entail DCPS functionalities. The Digital Twin software has a data connection to the data acquisition system and the PPC software and supports connection standards.

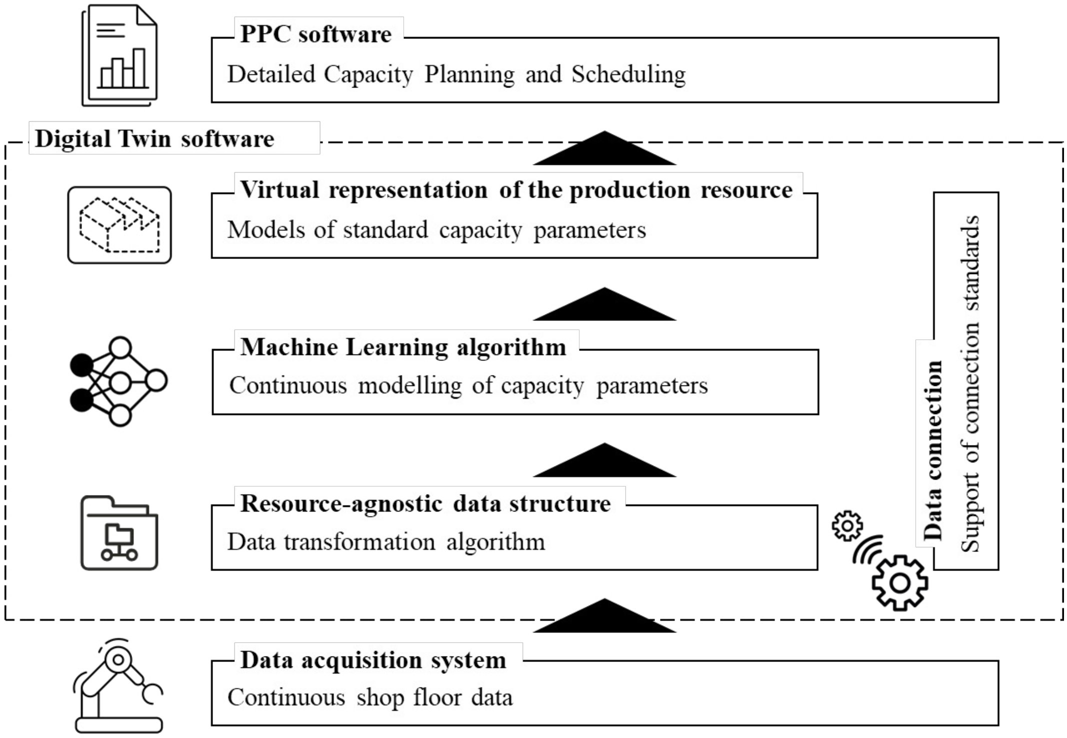

Fig. 3. Plug-and-play, Machine Learning Digital Twin of the production resource for DCPS (own figure).

5.1. Resource-agnostic data structure

The continuous shop floor data from the data acquisition system in the form of time series and event data is cleaned and constructed, and then recorded in a resource-agnostic data structure usable for the supervised Machine Learning algorithm. A data transformation algorithm automises these data preparation steps (R4.2). The resource-agnostic data structure entails the capacity parameters itself, as well as influencing factors. The influencing factors are recorded as numeric or categorical data that describe product properties, production parameters, and production conditions. Features are extracted from time series data of production conditions to ensure consistency between modelling and applying the models in planning. The data transformation algorithm is configured with the help of a configuration software component to reduce the scope of software coding. Before applying the Digital Twin software, influencing factors are selected which are known to be independent from other considered influencing factors and sensitive towards the capacity parameters. This dimensional reduction improves the confidence of the modelling result. Only influencing factors are selected that are available in the deployed PPC software or the virtual representation (R1.3). The manual steps of data preparation before applying the Digital Twin software are supported by the data preparation method, which describes the verification of the shop floor data quality, the selection of influencing factors to be recorded, and the configuration of the data connection and the data transformation algorithm.

5.2. Machine Learning algorithm

The Machine Learning algorithm automises the modelling of capacity parameters (R4.1). Supervised Machine Learning methods are suitable and mature to carry out regression analysis to determine models that predict parameters [37]. The Machine Learning algorithm maps expected values, distribution functions, and functions to correlating influencing factors for the capacity parameters as recorded in the resource-agnostic data structure (R3.1). If required the influencing factors are normalised, encoded, or discretised. The modelling is continuous and adapts to the continuous shop floor data (R3.3). Based on the resource-agnostic data structure, the uniform, generally applicable Machine Learning algorithm enables plug-and-play modelling of standard capacity parameters (R4.1). The Machine Learning algorithm does not presume a specific type of mathematical functions to correlating influencing factors for capacity parameters, and handles both numeric and categorical data for influencing factors. The Machine Learning algorithm establishes robust models of capacity parameters. When an influencing factor cannot be determined at the time of planning, or when no applicable data is available in the recorded shop floor data, the models provide adequate predictions (R2.2, R2.3).

5.3. Virtual representation of production resource

The virtual representation of the production resource predicts numeric data for capacity parameters regarding the production operations that are allocated to the production resource (R1.1). Standard capacity parameters include production time per unit, setup time, delay time, technical efficiency, and quality ratio (R2.1) [38]. The models of the capacity parameters predict expected values and entail multivariate functions to correlating influencing factors (R3.2). In the case of delay time, the model maps its distribution function. The influencing factors are determined by the PPC software or the virtual representation for the prediction of capacity parameters at the time of planning. The virtual representation provides standard capacity parameters that are applicable in various PPC software to enable a plug-and-play Digital Twin software (R4.2). The virtual representation also entails a resource schedule, resource capabilities, restrictions, and production costs (R2.4).

5.4. Data connection

The Digital Twin software entails a continuous data connection to the data acquisition system and the PPC software to automise data provision (R4.2). It is unenclosed, and capacity parameters are provided to other capacity planning tasks and their corresponding deployed software, such as factory planning or demand planning and rough scheduling (R1.2). The Digital Twin software enables plug-and-play connectivity with data acquisition systems and PPC software by supporting connection standards (R4.2). For data acquisition systems that do not support these connection standards, the Digital Twin software entails a configuration component that allows to integrate and format data without software coding. Interoperability is then enabled by the uniform, generally applicable data model.

6. Discussion

The proposed concept of a plug-and-play, Machine Learning Digital Twin aims to create and maintain a virtual representation of the production resource with a low level of effort and difficulty, while meeting the functional requirements of DCPS. It contributes to an intelligent production resource by providing self-assessment capabilities [39]. The personnel time and competencies required for the development of a specific Digital Twin software must not outweigh the benefits of an automated data provision, preparation, and modelling. The proposed plug-and-play Digital Twin software addresses that. The Digital Twin software can be extended for other functional areas, such as maintenance planning or quality management, by using the data connection to the data acquisition system and providing corresponding models of resource parameters to different software. It can be transferred to other types of resources, such as secondary production resources or logistics resources.

A more detailed specification and weighting of requirements depend on the specific application. E.g. the required accuracy may be relatively low when the logistical performance of a specific production system has a low sensitivity to the deviation from predicted capacity parameters. This can be the case when planning includes larger buffer times because work-in-progress inventory has relatively low costs. The consideration of influencing factors may not have to be required, e.g. to predict the production time in cycle time production. Also, constraints depend on the specific application, e.g. the quality of shop floor data may vary. Sensor technology usually provides more accurate and detailed shop floor data than manual data acquisition [8]. Low-volume production with high product variety may record a relatively low amount of shop floor data for specific factor values, and data-driven modelling may not reach a high confidence. Application prerequisite therefore influence the effectiveness of the proposed solution concept, and alternative approaches, e.g. a knowledge-based approach, may be advantageous. The requirements can be measurably specified, e.g. the mean deviation can be used as a metric to measure accuracy. This can support the required validation of the solution concept in empiric case studies. The presented requirements are stated from the perspective of DCPS and neutral towards a solution. More detailed non-functional requirements regarding the proposed Digital Twin software can be addressed before its development, such as response time, robustness, and resource efficiency.

7. Conclusion and need for research

In this article, the requirements regarding the virtual representation of the production resource for DCPS were compiled. The concept of a plug-and-play, Machine Learning Digital Twin was proposed to meet these requirements. The reviewed scientific literature does not describe sufficient findings to develop the proposed Digital Twin software, which have to be obtained by future research. A standard data model for an according resource-agnostic data structure is missing and has to be established [14]. The proposed data preparation method has to be formulated, which can include PPC-specific criteria for the verification of the shop floor data quality [40]. For the construction of structured data from time series data, feature extraction methods can be deployed, which describe e.g. means and peaks [41]. To design the Machine Learning algorithm, suitable Machine Learning methods have to be identified. Base methods such as Regression Trees, Support Vector Regression or Artificial Neural Networks can predict numeric data when categorical data is included in the influencing factors and the type of mathematical functions to correlating influencing factors is unknown [21]. They can be enhanced by Curve Fitting and Ensemble Learning methods such as Random Forest and Gradient Boosting. Additionally a method for continuously modelling capacity parameters can be adopted from the field of Continual Learning [42]. The modelling can e.g. be triggered periodically, or when the deviation of the predicted capacity parameters from recorded shop floor data increases anomalously. Suitable connection standards can be applied to enable a plug-and-play connectivity of the Digital Twin software with data acquisition systems and PPC software. These are e.g. the Open Platform Communications Unified Architecture, a connection standard for industrial resources, and the Asset Administration Shell, a connection standard and standard for the virtual representation of objects in the context of Industry 4.0 [43, 44]. A architecture has to be designed for the Digital Twin software that specifies components for data processing and storage and their communication. Concluding, a validation in empiric case studies has to be carried out with the implementation of demonstration software, along with the analysis of application prerequisites.

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