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Development and analysis of digital twins of production systems

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ABSTRACT
Production systems have to be adapted continuously to changing circumstances. This means that the responsible production planner has to frequently make decisions about reconfiguring complex systems under uncertainty whose outcome greatly affects the company's business success. Discrete-event simulation is one powerful tool to support the necessary analysis and scenario evaluation, but still remains time-consuming and tricky to set up and to maintain. When implemented as a digital twin of the production system, the simulation model can maintain a high degree of accuracy over a long time period. An approach to realise this potential is presented and illustrated in this paper with a use case from the automotive industry. This paper contributes several new methods and findings to the development of digital twins of production systems: Firstly, it demonstrates how exceptional events in the validation of the digital twin can be handled. Secondly, it shows how structural changes in the system can be discovered using data on machine activity and process mining. Thirdly, the paper introduces a possibility on how to assess the accuracy of the digital twin. Furthermore, it demonstrates how to assess the robustness of the digital twin to estimation errors in machine processing times.

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Digital twin; material flow simulation; data analytics; process mining; model validation

1. Introduction

Although product life cycles continue to become shorter, the necessary investment for modern production systems remains high. Therefore, a single production system has to be used for various product generations and variants, which implies many system changes during its life cycle. To ensure a high efficiency, continual analysis and optimisation of the production system are necessary. A promising tool for this task is material flow simulation (Mourtzis 2020). The downsides of simulation include a high initial effort in modelling and implementation as well as a substantial, continual effort to maintain the model and adapt it to changes in the real system (Bruckner et al. 2020). Currently, most simulation models in industry are abandoned after a project-based building and experimentation phase (Sitz et al. 2021; VDI 2014) which limits the benefits of the simulation model to a short time window (Neto et al. 2020).

The goal of this research is to address these limitations of simulation, by developing methods for regularly adapting a simulation model in response to changes in the system over its life cycle. The key enabler for this vision is the effective and automated use of existing data in production systems. Once the simulation can closely represent the real system during its whole life cycle, it becomes a digital twin which is the ultimate goal of our research. The term 'digital twin' is used in many areas and with different definitions and interpretations. We follow the understanding of Barricelli, Casiraghi, and Fogli (2019):

> A Digital Twin (DT) is more than a simple model or simulation. A DT is a living, intelligent and evolving model, being the virtual counterpart of a physical entity or process. It follows the lifecycle of its physical twin to monitor, control, and optimise its processes and functions. It continuously predicts future statuses (e.g. defects, damages, failures), and allows simulating and testing novel configurations, ...

To motivate and position the research, in section 2 we discuss existing work in automated or assisted simulation model generation and parametrisation, in the recognition of the structure of the production system for simulation models and in the discovery of the dynamic behaviour of the system. In section 3, we introduce the real-world use case from the automotive industry that serves as the test bed for the research. Then the contributions of this paper are presented in section 4. These contributions include methods to address exceptional events during validation, to discover structural changes

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in the system and to monitor the accuracy of the digital twin over time. To highlight data requirements, limitations and possible benefits of these methods, we present a sensitivity analysis as well as examples of their usage in operations. The paper closes with a summary and some further research questions.

This paper builds upon and extends prior publications that explain the concept and certain aspects of the digital twin of production systems (Brützel et al. 2020; Overbeck, Brützel, et al. 2021; Overbeck, Le Louarn, et al. 2021). These publications explain the underlying simulation model, and present mechanisms for parameter computation (i.e. process times, availability, and scrap rate), for discovering the material flow, for the calculation of accuracy metrics, and for automated validation and update of the simulation. We will summarise these prior developments when necessary for the understanding of the new contributions of this paper. In this paper, we extend some of the earlier mechanisms (considering exceptional events during validation, discovering structural changes), and we examine the behaviour, accuracy and use of the digital twin, over time and with changing data quality.

2. Literature review

For the creation of digital twins of productions systems various streams of research are relevant. In the following, we do not provide an exhaustive review of the literature but discuss important and representative works as a way to present an overview over the different research perspectives on this topic.

2.1. Simulation and digital twins

One stream of literature considers simulation, particularly material flow simulation, as a tool for production planning. Similar papers exist for the subject of digital twins, often in combination with definitions and/or classifications to gain a better grasp of this concept. An extensive study on the usage of simulation for production planning and control under consideration of the different tasks is given by Jeon and Kim (2016). It is shown that discrete-event simulation (as used in our approach) is recommended and predominantly used for the vast majority of tasks in production planning and control. One new and increasingly important application of simulation models is the training of machine learning algorithms; Kuhnle et al. (2021) argue that the simulation model has to be as realistic as possible to facilitate the transfer of the trained algorithm from the training environment to real production, which can be achieved by its transformation into a digital twin. One of the objectives of digital twins in manufacturing is often to increase the robustness and the resilience of the system (Preuveneers, Joosen, and Ilie-Zudor 2018).

A frequently used concept of Stark, Kind, and Neumeyer (2017) divides the digital twin into a digital master, which is an abstract description of a class of things, and the digital shadow, the collection of all data related to a concrete instance over its entire lifecycle. If the abstract digital master is now linked with the digital shadow of an instance, this creates a digital twin. This definition can be applied to our approach as well but is not uncontested in literature. Detailed literature reviews and structuring approaches on the topic of digital twins in production are provided by Kritzinger et al. (2018), Cimino, Negri, and Fumagalli (2019) and Lechler et al. (2020). A common understanding of digital twins across this literature is its description as 'a digital representation with data connection that enable convergence between the physical and digital states at an appropriate rate of synchronisation' (ISO/IEC JTC1-SC41/300/CDV ISO/IEC 30173 ED1: 2022), which also complies with the approach of this paper. A compilation of the different characterisations of digital twins can be found at Jones et al. (2020). Among other issues, they identify the maintenance of the digital twin over the entire system life cycle as well as its technical implementation as research gaps. These open questions will be considered in this research.

There are numerous works on (partially) automated or at least supported simulation model generation. In the following, the existing foci are grouped together and exemplary publications are given.

2.2. (Partially) automated model generation and parametrisation

In 2002, Werner and Weigert published an approach for continuous optimisation of production planning based on in-process simulation using discrete-event simulation and production relevant data from ERP and Production Data Acquisition (PDA) systems. The application of an error metric (error in terms of duration or start time of an event) allows continuous analysis and monitoring of the discrepancy between simulation model and real production. In case of a discrepancy, the model parameters can thus be adjusted to the real conditions.

Müller-Sommer (2013) focuses in his dissertation primarily on the automated plausibility check of input data for intralogistics simulation models. He considers the quality, correctness and completeness of input data as critical factors for the efficient generation of simulation models.

SISO (Simulation Interoperability Standards Organization) published the Core Manufacturing Simulation Data (CMSD) standard in 2010 to standardise data exchange between enterprise and manufacturing IT systems and simulation software (SISO-STD-008-2010). Based on this, Skoogh, Johansson, and Stahre (2012) presented a tool for Generic Data Management, which is able to output arbitrary data from different sources in XML format (Extensible Markup Language) according to CMSD standard.

Bergmann (2013) used the CMSD standard for automatic model generation in his dissertation. In the developed overall architecture, simulator-specific model generators are required, two of which are created for the Plant Simulation and SLX simulators. Interfaces to enterprise software are discussed only superficially. Validation was performed in both laboratory and field experiments. Neither approach has yet been found in practice, as the CMSD standard has still not gained broad acceptance (Bergmann and Straßburger 2020). Leng et al. (2019) discuss the update of the digital twin using real data for parallel controlling.

A literature review on recent work on automatic simulation model generation focusing on information retrieval was done by Reinhardt, Weber, and Putz (2019).

2.3. Recognition of the system structure

Less work can be found in the field of system structure recognition for simulation models. Jensen (2007) presented in his dissertation a methodology for the semi-automated generation of simulation models for material flow systems using the XML format. A more comprehensive approach in terms of different levels of detail is taken by Thiers et al. (2016). They automated simulation model generation in commercial software for an aircraft manufacturer by enabling translation between different models with different levels of abstraction. Thus, there is no longer a distinction between parameter and structural changes. Modelling, however, is still necessary – at a higher level of abstraction. More abstract is the *Virtual Factory Data Model* developed by Terkaj and Urgo (2015) which can be used to generate abstract simulation models of production systems using an ontology and real data maintained according to this ontology. Leng et al. (2020) use a digital twin to validate the performance of reconfigurable automated manufacturing systems using a standardised hardware platform. How a digital twin can be used to rapidly design manufacturing systems is illustrated by Liu et al. (2018). Because up-to now the automated recognition of system structure for the simulation of production systems remains unsolved, the presented research tackles this issue.

2.4. Derivation of dynamic behaviour

A central challenge for the completely automated digital twin remains the learning and adaptation from the dynamic behaviour the production system. Selke (2005) focuses in his dissertation on the automated integration of processes and strategies of production planning and control into the automatic generation of operational simulation models. He develops an automated interpretation of sequences and strategies using pattern recognition in operational data, with clustering based on a priori expert knowledge.

Zenner (2006) describes that automatic model generation from process graphs supplemented by resource information is only possible under tight constraints, which is mainly due to the insufficient representation of dynamic behaviour. Rozinat et al. (2009) take a more data-driven approach and combine various aspects of process mining to automatically create a simulation model as a coloured Petri net based on event logs.

In Bergmann, Feldkamp, and Straßburger (2017), the authors summarise their previous activities for the automatic emulation of dynamic processes or rules for simulation models. They distinguish between manual mapping, matching of real data with a set of predefined rules (e.g. using pattern recognition) and machine learning methods that try to imitate the behaviour. A comparison of the various learning methods for the approximation of dispatching rules using a simple example is given in Bergmann, Feldkamp, and Straßburger (2015).

2.5. Deficits in the state of research

As shown above, the supported or automatic generation of simulation models in the production environment has been an aspiration for decades in order to make simulation more easily accessible to users (Lugaresi and Matta 2021). In order to achieve the full potential of digital twins, we need a way to recognise system changes and automate the update. We therefore pose the following three requirements as necessary to transform the existing simulation model into a digital twin of the production system:

R1: Offer algorithms and methods for data extraction and for processing and analysis to discover changes in the parameters, structure and dynamic behaviour of the production system.

R2: Provide mechanisms for achieving model convergence to reality, including methods for automatic validation and updating of the simulation model based on real data.

R3: Include an analysis of the behaviour of the digital twin in relation to the real system over time and an assessment of its robustness to data availability and quality.

Previous work has been able to automate individual aspects, but a holistic, cohesive framework that is easy to apply in industry does not yet exist. While many prior papers do report on real use cases from industry, most of them are missing an extensive and repeated validation of the simulation model against reality. Without this repeated comparison to reality, one cannot really establish that the simulation is a digital twin. The focus of most prior papers is on the completely automated creation of simulation models.

Table 1 compares the current state of research presented above with the three research requirements. If a cited paper explicitly addresses a certain aspect, the circle is marked completely black; the circle is partly filled if the paper substantively discusses the aspect, and is blank when the aspect is not considered. Review papers are not included in the tabular summary. From the table, we see that the prior research does not completely answer all of the research questions, and hence, further research is warranted to enable digital twins of production systems to be used on a broad scale.

3. Use case and problem statement

In this section, we present our research in the context of a real-life use case and its corresponding challenges. We consider a production system of the Bosch Powertrain Solutions division, which does final assembly and testing of combustion engine components. Many changes are predicted in the car engine market in the near future, including scenarios with an increasing number of product variants while overall production volume decreases. To accommodate these changes, the production system at hand will have to be frequently modified and these modifications to the production system will have to be performed with limited funds as the system reaches its end of life. Other production systems in other companies might face completely different scenarios but still are required to change often in light of uncertainty.

A discrete-event, material flow simulation model of the production system was built by simulation experts (Brützel et al. 2020). With this simulation, experts could perform analyses of the current system, as well as examine scenarios and improvement measures, following the typical work mode of simulation projects as described in VDI (2014). To make the model usable for an extended time period will typically require continuing maintenance efforts by the simulation expert(s) who built the initial model. However, this is expensive and an inefficient use of time and expertise of the simulation expert. Rather, we propose to transform the simulation model to a digital twin of the production system, which will adapt to changes over the life cycle of the production system. The objective is not to have a real-time synchronisation between the real system and the simulation but rather a less-frequent automated validation, which might be performed for example once a week and which might trigger an update, if the validation result is negative.

Table 1. Related literature and research requirements.

Research requirements	R1 Data processing and analysis			R2 Convergence capabilities			R3 Analysis of convergence		
Aspects of research requirements	Parametrization	Structure	Dynamic behavior	Automated validation	Automated Updates	Applicable on real data	Convergence behavior	Influence of data quality and availability	Validation on real use case
Werner et al. 2002	●	◑	○	◑	◑	◑	◕	○	●
Müller-Sommer 2013	◕	◑	◑	○	◑	◔	○	◑	●
Skoogh et al. 2012	●	○	○	○	◕	◕	○	○	●
Bergmann 2013	●	◕	◑	○	◔	◔	○	○	●
Leng et al. 2019	◕	◑	◑	◑	◕	◔	○	○	◑
Liu et al. 2018	●	◕	◑	◔	◕	●	○	○	●
Jensen 2007	◑	◑	◑	○	◔	◑	○	○	●
Thiers et al. 2016	◔	◑	○	◔	◕	◕	◔	○	●
Selke 2005	○	○	◑	○	○	◑	○	○	●
Rozinat et al. 2009	◑	◑	◑	○	○	◕	◕	◔	●
Bergmann et al. 2015	●	◔	◑	○	◔	◔	○	○	◔

● = completely fulfilled ◑ = discussed ○ = not considered

3.1. Description of production system

In the plant under consideration, there are multiple similar production lines that produce a product needed for internal combustion engines. Each production line consists of a final assembly area, where the parts of the component are put together, and a testing area, where functional tests and finishing steps are performed. The arrangement of the two areas is shown in Figure 1. The target number of employees per subsystem is n for assembly and m for testing and depends on the product variant and required production volume. The production is organised according to the chaku-chaku principle, in which employees are responsible for loading and unloading the individual parts into and out of the machines, while the actual process is largely automatic (Krugh et al. 2017). In some areas of the production system, the employees are also responsible for transporting the product between machines or buffers, while in other areas the transport is automated with a conveyor system.

The lines of the plant differ in individual machines and thus can produce different product variants for different engines and different customers. We developed a digital twin for one of these lines following the approach outlined in this paper and then this digital twin was transferred to the other lines.

Production is normally planned to run all day. However, a production line will often shut down for a particular shift, e.g. due to a lack of demand, insufficient employees or a lack of material.

3.2. Description of simulation model

In the simulation model of the production system described above, we do not model the material supply, as we assume that there are always enough parts at the stations. In addition, we assume that there are no interactions between the production lines and thus, they can be studied independently. The simulation model for each production line has an internal central data storage, which contains its parameter values, as well as behavioural and structural information (such as employee loops, routing table, buffers and conveyor belts).

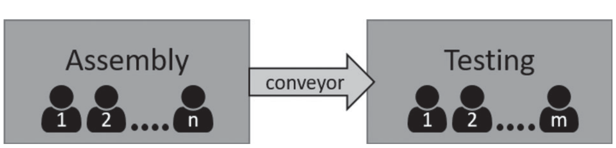

Figure 1. Structure of the production line.

3.3. IT systems

All relevant production data is gathered by a manufacturing execution system (MES) and stored together with other data from various IT-Systems (i.e. Enterprise Resource Planning (ERP)- and Quality-Management-Systems (QMS)) in a central data lake (Khine and Wang 2018) for further analysis. We can then obtain the data for the digital twin from the central data lake using SQL (Structured Query Language) Queries, which can be automatically adapted to the current state of the digital twin.

4. Contributions to digital twins of production systems

4.1. Overview of approach and contributions

Our solution approach follows the model maintenance and usage cycle shown in Figure 2. The existing simulation model (which is created by a simulation expert) is validated by comparing its behaviour in a past time period with the behaviour of the real system in the same period. If the deviation to reality is too big, then the fidelity of the model is too low and an update of the model is triggered.

Following Stark, Kind, and Neumeyer (2017) the initial model can be considered the digital master of the production system and the integrated information the digital shadow, together forming the digital twin of the production system.

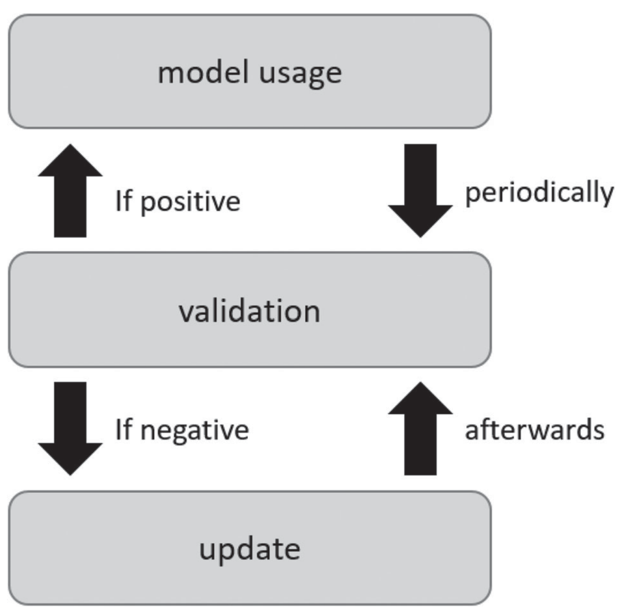

Figure 2. Digital twin mechanism – model maintenance and usage.

The methodology was implemented in the industrial setting at Bosch using Tecnomatix Plant Simulation from Siemens as simulation software and the programming language Python for the data acquisition and processing. The initial modelling of the production system (initial seed model) is based on Brützel et al. (2020). Since not all elements of the digital twin can be automatically adjusted for all possible changes, user interaction may be necessary. That is, if a deviation to reality cannot be resolved automatically, it might be necessary to alert the user that the digital twin is no longer up to date and to point to possible causes for the deviation. The validation and update mechanism does not have to be very fast, because the digital twin of the production system is not supposed to be updated in real-time. Its application is more on a strategic-/tactical scope. Therefore, the validation mechanism can be performed for example once a day, week, or month and a runtime of a few minutes or even hours is not critical.

In the use case, the machine process times, scrap rate and machine availability were obtained and processed automatically as described in Overbeck, Le Louarn, et al. (2021). The material flow was captured automatically using process mining and the approach detailed in Overbeck, Brützel, et al. (2021).

4.2. Addressing exceptional events in validation

As noted in section 2.5, the validation of the underlying simulation model is often treated only superficially. In this section, we propose a series of mechanisms to automate the model validation.

4.2.1. Overview of validation mechanism

In order to validate the digital twin, a procedure for automatic comparison of the simulation model with the real system is necessary. For an efficient, automatic validation, we require detectable and meaningful key performance indicators (KPIs) to measure the fidelity of the digital twin, which we will call accuracy metrics. Examples of possible accuracy metrics are the relative prediction error (RE) of the aggregated system output in the period under consideration (Formula 1) or the normalised root mean squared error (NRMSE) of the outputs over time (Formula 2).

$$\text{Relative error} = \frac{N_{real} - N_{Sim}}{N_{real}} * 100 \tag{1}$$

with N_{real}, N_{sim} being the total number of parts produced at the end of the studied period in reality and in simulation, respectively.

$$\text{NRMSE} = \frac{100}{\bar{x}_{real}} * \sqrt{\frac{\sum_{i=1}^{N} (x_{real,i} - x_{sim,i})^2}{N_{real}}} \tag{2}$$

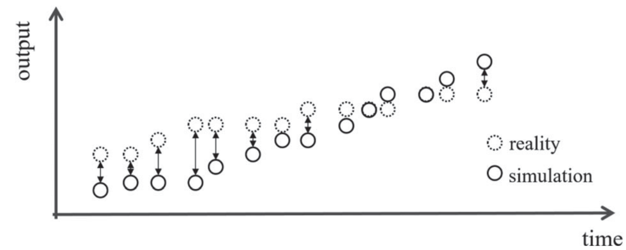

Figure 3. Cumulative output $x_{real,i}$ and $x_{sim,i}$ as used in calculation of NRMSE.

with $\bar{x}_{real}$ being the average real output per time period and $x_{real,i}$ and $x_{sim,i}$ being the real and the simulated cumulative output at time i. N_{real} is the number of observations. To compute NRMSE, one makes an observation at each time epoch at which either a part is finished in reality or a part is finished in the simulation. Hence, the interval between two observations is not constant (see Figure 3).

As discussed in Overbeck, Brützel, et al. (2021) we set the threshold value for model validation to ±3% for the relative error and ±5% for NRMSE. For a more detailed discussion of accuracy metrics please refer to Overbeck et al. (2022).

Besides these accuracy metrics, there are many other considerations when setting up the validation. Some important considerations are the determination of the validation period for comparison, the possible exclusion of extraordinary events in the validation period, the number of simulation iterations, and the trigger measure (e.g. how often and by which event) for the validation of a digital twin.

Concerning the validation period, we chose a time horizon of one week (7 days) for the use case, because this is the typical horizon for production planning at this plant. It is long enough to include production of several different product variants yet remains short enough to allow multiple simulation iterations in acceptable time for the user.

We discuss next the consideration of exceptional events during the validation period. For the other considerations, we will illustrate later how they have been handled in the use case.

4.2.2. Exceptional events during validation period

To compare the simulation runs with the real system behaviour, we must transfer or apply the actual conditions during the validation period to the model. This includes the availability of employees, the transportation system or material (if these are not modelled in the system itself with probabilistic distributions), as well as various aspects of the production plan: the variants to be produced, their quantities and the production breaks. For a reliable validation, we must also account for extraordinary events, that occurred and affect the system behaviour and that are not captured by the simulation. That is, these events are not in the simulation as either normal behaviour of the system or probabilistic events. Examples of exceptional events include exceptionally long failure events, new failures not foreseen in the model itself, or organisational 'disruptions,' such as ad hoc staff meetings or trainings. In such instances, we first need to recognise such extraordinary events from the available operational data in order to carry out a validation automatically. The challenge to identify these events depends on the characterisation of 'normal' system behaviour. Every machine in the simulation model has an availability and mean-time-to-repair, which are calculated on the basis of real data for the digital twin. To accurately estimate model parameters and perform validation, it is crucial first to decide which failures are extraordinary and which are not and then to decide how to use (or not use) the extraordinary failures in the parameter estimation and validation.

In order to recognise extraordinary events from the available data, one might differentiate according to the event type. For this, however, these types must be known in advance and contained in the data, and all historic events must be labelled by type in advance by an expert. However, these prerequisites will not always be possible; furthermore, new, unassignable events can occur during operation despite extensive declaration ex-ante. Hence, it seems better to distinguish events based on the temporal length of the event, since this information is captured in most cases during data acquisition. We propose to do this with a threshold t, which defines the maximum duration of normal failure behaviour. Observed failure instances that are smaller than t will then be considered normal failure behaviour and used for availability calculation and parameter estimation. Events with a duration longer than t will be considered as extraordinary; these events will not be used for parameter estimation but rather be included as explicit events within the simulation when performing validation simulation runs.

To determine the threshold t, there are two possibilities: based on historic data or based on simulation experiments. Both will be discussed in the following.

4.2.2.1. Based on the historical occurrence of events. In our use case, machine failure data is collected automatically from the machine controller to the central data lake. In addition, the supervisor is required to document all events that lead to a direct production loss at the last station of the production line. Long machine failures therefore might appear in the documented exceptional events and in the automatically registered machine failure data.

Based on the available data, we can compile a distribution of the duration of the registered machine failures in the past. The threshold value t *is* now to be chosen in such a way that the exceptional failures are quite rare, and that the normal failures account for as much of the cumulative failure duration as possible.

The historic failure data for 3 months is aggregated by duration in seconds in Figure 4. When looking at the distribution of number of failure instances and total failure duration, it seems reasonable to choose a threshold value of 120 s, because 99.4% of the failure instances and 83.5% of the total failure duration correspond to failure instances with a duration shorter than this. Figure 5 shows the distribution of exceptional events electronically documented by the supervisor. It indicates that 80.8% of these documented exceptional events have a duration longer than 120 s and these account for 96.8% of the total duration for these events. All these high percentages make 120 s look like a good candidate for t.

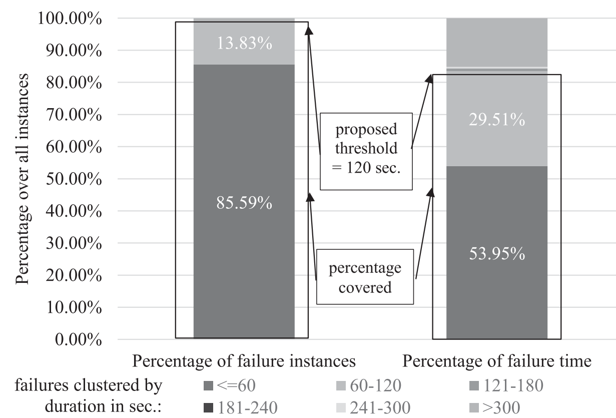

Figure 4. Historic distribution of registered machine failures clustered by duration over 3 months on one line.

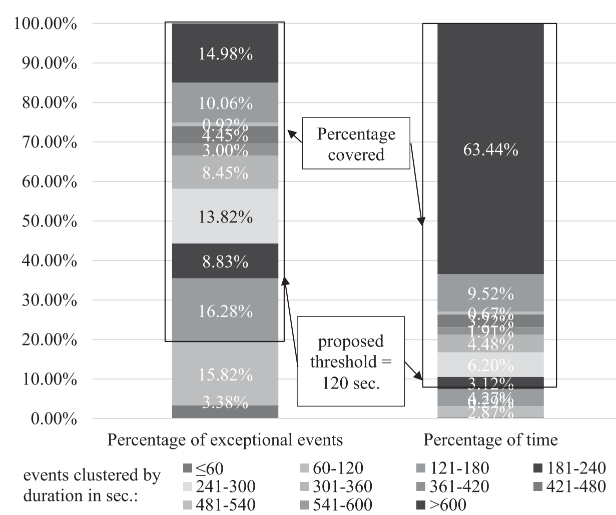

Figure 5. Proportion of instances and of total standstill time caused by supervisor-documented events clustered by event duration in second (historic data of three months on one line).

Table 2. Example of empirical analysis of suitable threshold for the definition of exceptional events (EE).

Threshold value t (min)	Number of failures	Number of EE	Relative error assembly (%)	Relative error testing (%)
2	123	102	0.60	3.16
3	127	73	0.51	3.30
…	…	…	…	…
15	129	7	0.0	2.61

4.2.2.2. Based on simulation experiments. To get the best possible choice of t, we can test all candidate values by simulation to see what results in the highest validation measures. Table 2 gives an example how the empirical analysis for setting the right threshold values can look like. The update and the validation step are performed for a given time period using different threshold values and the resulting relative error for the two subsystems are compared. Based on the simulation results, we can then identify the best threshold value in this case as $t = 15\,\text{min}$.

Because the analysis of the historical failure data indicated a smaller threshold value of $t = 2\,\text{min}$, a decision must be taken, considering all information at hand. In the use case of the automotive supplier we set a threshold of 15 min, because this higher threshold value results in a higher proportion of failures being considered for parameter estimation and in having fewer events explicitly specified during validation runs, leading in sum to a higher generality of the simulation model. Therefore, the higher threshold was chosen. Although there now are very few exceptional events, these very long events have a significant influence on the system behaviour and must be explicitly included in the validation runs.

One possible reason why the higher simulation-based threshold gives better accuracy could be that the simulation model has a better generalisation capability than expected, in that events with long failure time are already indirectly incorporated into the model through their effect on parameters that are directly considered in the model.

4.3. Discovering structural changes of the system

Earlier publications have reported on the determination of parameters and dynamic behaviour (Overbeck, Brützel, et al. 2021; Overbeck, Le Louarn, et al. 2021). In this paper we consider the handling of structural changes, which has not been considered in the prior research (see section 2.5). We present and test two ways to discover structural changes of the production system using different data sources.

4.3.1. Based on historic data of machine activity

Layout information is often available only in file formats such as.dwg-,.pdf-, or even.jpg-formats that are difficult to analyse automatically and adapt dynamically. Therefore, and because the layout files usually represent some planning status that has not always been adapted to reality, we attempt to use real data from the operation of the production system for recognising structural changes. From the production data, we have timestamps for the production of each part on each machine. Therefore, we can discover within a time period whether a machine has produced any parts or not.

In this manner, the digital twin can recognise when new machines have been commissioned in production. As soon as a new machine produces its first product, the digital twin can recognise this and can then include this new machine (even if there is insufficient data to estimate the machine parameters such as scrap, availability and process time).

When a machine is taken out of operation, it can be more challenging to detect the change, and especially to determine the time of decommissioning. A machine can still be available even if it has not been used for a long period of time. In the proposed approach, we set a limit value on how long a machine needs to be idle before we regard it as inactive in the simulation model (e.g. one year without a produced part on the machine). However, even with such a rule one cannot exclude errors, so one might also alert the user to compare the structure of the real system with the simulation model. Furthermore, within the simulation, an existing but unused machine in the production system usually has no great influence on the system behaviour.

With this approach, we can use real data to identify any structure changes in the production lines of the use case (which have machines types denoted by M1–M30) prior to the implementation of the digital twin. In Figure 6, we show the times at which machines were added or removed from each of the production lines in the prior eight years. Because the lines under consideration are all in one facility, we can also make some presumptions about the relationships between these lines. For example, when a M7 machine is removed at line 1 and several months later appears at line 3, it is probable that the machine was moved there. We observe instances where multiple new machines are added in one line at the same time. We can also see that after a machine 12 was added to line 2, line 3 added one too. It is also interesting to see that machines 11 are removed from line 2 and 3 around the same time. We can use these inferences to facilitate the parameter estimation by comparing the data of the machine at the new line to the data for this machine at the old line.

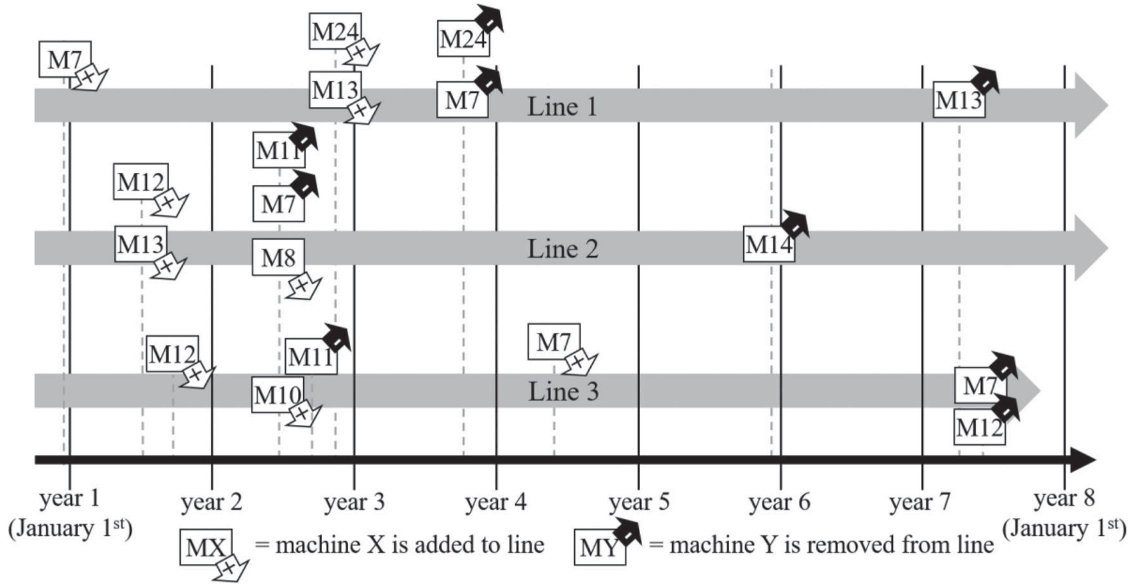

Figure 6. Examples of observed historic structure changes in the production system.

4.3.2. Based on observed material flow from MES data

The information about new or removed machines should be supplemented by their position in the material flow. If we can recognise the material flow automatically from the available data using process mining as described in Overbeck, Brützel, et al. (2021), we can derive from it detailed insights about the structure of the production system. Thus, with sufficient resolution of the data points, we can obtain information not only on the stations used, but also on the workplaces inside one station when multiple products can be in the station at the same time.

To determine the material flow, we use the alpha algorithm from van der Aalst (2016, 171). However, it is important to adjust the filter settings: when it is used to obtain the material flow for a certain product variant to feed into the simulation model, the raw event data is pre-processed using various filters on process flow length, most common start and end processes and loops. These filters must be set quite narrow to identify only the main product flow. However, to check for changes in the machine layout, one needs to uncover a broader set of material flows, not just the dominant material flow. Therefore, filters on process flow length, frequency, start and end process should be relaxed (van der Aalst 2016, 416).

We show examples of the changes of the material flow observed in the data on one line over four years as Petri nets in Figure 7(a–d). The event data used for the analysis is not aggregated on a machine level but provides a greater level of detail as it encompasses the timestamps of the process start and end points on working and tool positions inside the machines (second part of the identifier). This allows the digital twin to observe changes even inside machines on a great granularity. We can observe that most of these changes do not concern complete machines but low-level units. We can observe changes in the number of production steps (a, b and d) as well as changes in the arrangement of the existing ones (c). When looking at parallel process steps, it is important to distinguish between process alternatives (e.g. (d)) and cases in which both parallel processes have to be completed before the next process can be performed (e.g. (b) and (c)). In (a) the process step at work position M8.1 was added after M7.3 and before M8.2. In (b) the process step at work position M11.3 was added as necessary, but it can be performed at the same time as process step M11.2. In example (c) the strict sequential order of the process steps M9.1 and M9.2 was relaxed. The resulting process flow is identical as in case (b) but comes from a different prior state. Example (d) shows the addition of a new alternative process step M4.2 which can be performed instead of M4.1.

Both approaches detailed above could be successfully applied to identify historic changes in the production system and will be capable of doing so in the future and then trigger an alert to the user of the digital twin to update the corresponding structure items.

4.4. Observing accuracy over time

We observe the accuracy of the digital twin for a single production line in multiple validation periods measured with the mean relative error of the total produced output over the validation period (here always one week) and the NRMSE. The results are given in Table 3 for

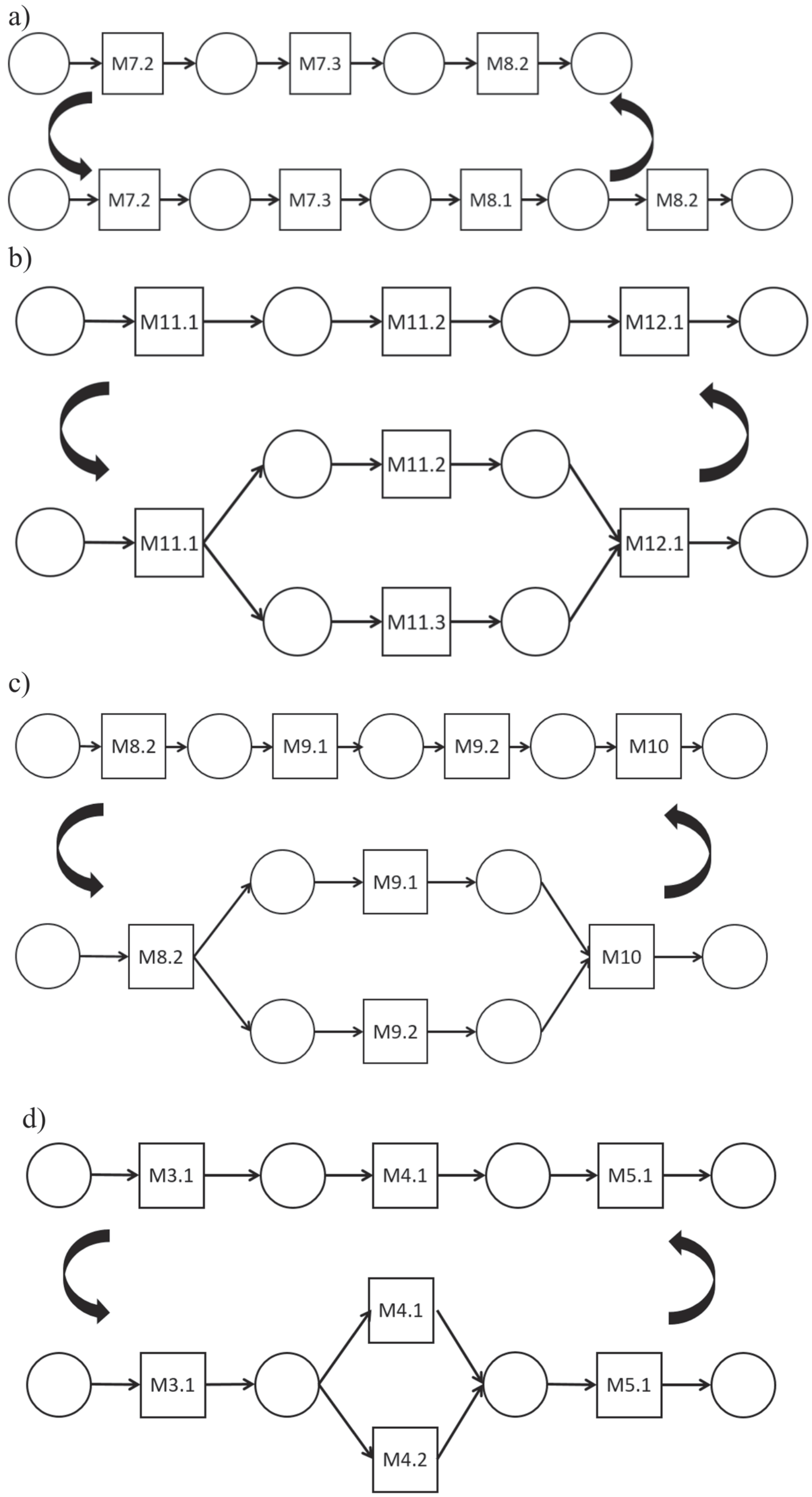

Figure 7. a–d. Examples of observable changes in material flow that indicate changes in the production system. (a) Add/remove sequential process step. (b) Add/remove required parallel process steps. (c) Change between sequential and parallel (both required) process steps. (d) Add/remove alternative parallel process steps.

Table 3. Validity of digital twin over time before and after update.

		Mean relative error (in %) + 95% confidence interval		NRMSE (in %) + 95% confidence interval	
		without update	with update	without update	with update
Week A	Assembly	4.32 (±0.61)	1.16 (±0.37)	6.09 (±1.12)	2.11 (±0.68)
	Testing	5.02 (±0.61)	0.90 (±0.48)	7.96 (±1.12)	3.18 (±0.84)
Week B	Assembly	3.42 (±0.29)	1.30 (±0.99)	4.79 (±0.61)	4.39 (±1.62)
	Testing	6.03 (±0.42)	1.56 (±1.58)	5.02 (±0.60)	5.00 (±2.34)
Week C	Assembly	7.83 (±3.99)	6.06 (±2.90)	5.08 (±1.89)	4.21 (±1.09)
	Testing	9.97 (±3.42)	8.00 (±2.61)	7.11 (±1.93)	5.38 (±1.65)

three consecutive weeks A, B, C. Each validation is performed with 10 simulation runs and the 95% confidence interval is given. 'Without update' refers to the simulation model parametrised with data from older time periods (respectively the initial data set for week A), 'with update' refers to a simulation model updated with the last available data at this point in time. Week A without the update is parametrised using the initial data set, that was defined during the model creation. Because week A is already a few months after the initial model creation, the update improves its accuracy. From the Table, one sees that a repeated update of the digital twin is needed in order to maintain a high accuracy of the digital twin over time.

4.5. Sensitivity analysis of digital twin

The digital twin in our use case was constructed with a large amount of high-quality data. In other settings this may not be the case, and the question arises whether it is possible to achieve satisfactory accuracy when we have less data or data of lower quality (error-prone or biased). In other words: Can our digital twin approach be successfully applied in contexts which do not have a high level of digitalisation yet (for example SMEs)?

In the following, we show how one might assess the sensitivity of the digital twin. In particular, we conduct a sensitivity analysis to demonstrate how the estimate of the machine process times affects the accuracy in the use case. Because the relative error only considers one single point in time (the end of the period), the NRMSE proves to be a more stable and therefore, a more meaningful measure for accuracy of the digital twin since it aggregates information over the whole time period.

For this analysis, we assume a normal or lognormal distribution for the machine process times, with mean and standard deviation estimated from the data. In Figure 8, we report the average NRMSE when we vary the mean (standard deviation) of the machine process times

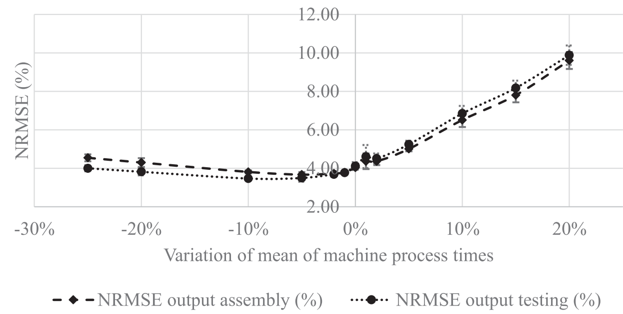

Figure 8. Sensitivity of NRMSE on variation of the mean of machine process times including the 95% confidence interval.

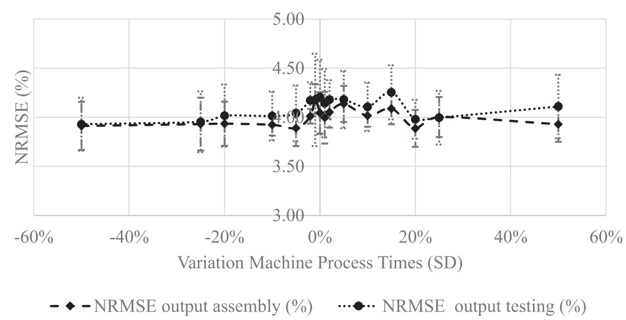

Figure 9. Sensitivity of NRMSE on variation of the standard deviation of machine process times including the 95% confidence interval.

including the 95% confidence intervals. For each observation, we performed 10 simulation runs. The confidence intervals are between ± 0.06 and ±0.6. From Figure 8, we see that the accuracy is very sensitive to overestimating the mean of the process times, and much less sensitive to underestimating the mean.

However, in Figure 9 the fidelity of the digital twin seems insensitive to errors in the estimate of the standard deviation of the machine process times of up to ±50%. This means that the decrease in fidelity observed in the first analysis can the attributed to the change in the location parameter of the distribution not its spread parameter. Small alterations lead to a change in the system behaviour but without a clear indication whether it becomes more or less accurate. This indicates that these spikes are caused by the intrinsic volatility of the system and its model. Here the 95% confidence intervals are between ±0.11 and ±0.47.

In the next step of the analysis, we modify the mean and standard deviation for all of the machines by ±x% together. We vary x from –25% to +20% with step size of 5% and smaller steps around zero (±1%; ±2%). Again, we performed 10 simulation runs per experiment. In Figure 10, we show the results for the assembly and the testing subsystems and find that the accuracy of the digital twin decreases significantly when the mean and the

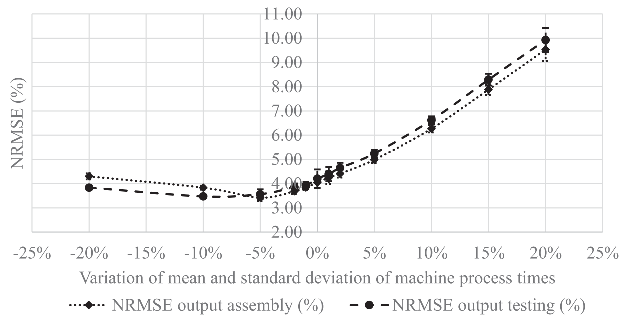

Figure 10. NRMSE for different variations of mean and standard deviation of machine process times including the 95% confidence interval.

standard deviation are simultaneously changed for all machines in the line by more than ± 5%. The NRMSE does not continue to increase on the left side as on the right side; as the process times are reduced, at some point the worker become the system bottleneck and the system output no longer increases. The reported 95% confidence intervals are in this case between ±0.06 and ±0.49.

In Figure 10, we see a behaviour similar to that when we vary only the mean (Figure 8) confirming our observation from Figure 9 that the variation in the standard deviation has no influence in the accuracy.

4.6. Benefits of the digital twin for production planning and control

The digital twin of the Bosch production lines was used in various occasions over a time period of multiple years to evaluate different scenarios and actions to improve productivity, or to react to changing external conditions, or to prepare for future changes (e.g. introduction of new product variants). The benefit of evaluating proposed decisions beforehand is not always easily quantifiable (Andreasson et al. 2019), but in the following example we shall illustrate the potential of a digital twin of a production system to inform decision making. The digital twin used in the following analyses did not yet include all the extensions presented in this paper, but did incorporate at least all features described in Overbeck, Brützel, et al. (2021) and Overbeck, Le Louarn, et al. (2021).

One possible future scenario includes a declining demand for the produced product. This would lead to an underutilisation of the existing production lines. The planning objective therefore changes from achieving the highest machine utilisation to produce as much as possible, to producing the required amount with the least cost possible. This can be realised by a reduction of the number of active workers in the line. Fewer workers in the line will increase the planned cycle times for each product variant; however, it is challenging to predict what exactly these cycle times will be. Consequently, the manpower planning for the next year becomes less accurate and reliable; therefore, to accommodate this uncertainty, this results in overstaffing, leading to extra costs. This overstaffing can be prevented with the digital twin, which enables a more accurate prediction of the cycle times and therefore, better manpower planning. With the use of the digital twin, we performed simulation experiments with one to x workers in each subsystem for each product variant that will be produced in the considered time horizon. These experiments resulted in precise estimations of the actual cycle time for each staffing level for each variant. These estimated cycle times could be used to identify the staffing level needed to produce the required quantities in the given time. We found that the planned work force could be reduced by 12% and the production targets should still be achievable.

In addition to support for longer-term tactical decision making, the digital twin can be used for short-term operational questions, including verification of today's production plan (including variant mix), allocating the present worker to the right areas, and defining best timing of setups.

5. Outlook and conclusion

We present an approach to transform expert-made material flow simulation models into digital twins of production systems. This approach entails using real production data and automatic validation, along with updating mechanisms, to convert a one-shot capture of the system into a life-cycle digital twin of reality. The approach satisfies the defined requirements, because it offers data analysis methods to discover changes in the parameters, structure and dynamic behaviour of the production system (Requirement R1), provides mechanisms for automatic validation and updating of the simulation model (R2), and includes an analysis of the accuracy of the digital twin over time and of its robustness to data availability and quality (R3). It was successfully applied to a real-world use case, where it led to (1) an increased accuracy of the model, (2) longer validity of the model over time, (3) reduction in expert effort for model maintenance and (4) successful application of the model for production planning. The industrial use case was also used to examine the data requirements for building such a digital twin using a sensitivity analysis. The results indicate that the digital twin is robust to small errors or biases in the data.

These promising results suggest further research questions concerning the successful integration of such a digital twin in the processes of production planning and control. It would be of interest to understand what organisational changes are necessary to maximise the benefits from a digital twin. Furthermore, because many simulation models are built during the planning phase of new production systems (often early and with little detail to begin with), it would be desirable to prepare these models in such a way that they could be turned into digital twins of the real systems once the production system is planned, built, commissioned and running. Requirements and methods for this transition have to be developed. It would also be interesting to examine the effect of integrating digital twins on different levels, i.e. of plants, machines, or complete production networks on the accuracy of each digital twin.

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Data availability statement

The data that support the findings of this study are available from the corresponding author, L.O., upon reasonable request.

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