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Backlog control in optoelectronic production using a digital twin

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Abstract

Digital twins are becoming increasingly popular in industry and are being used in various areas, such as production planning and control. Logistics performance still needs to be improved, especially in highly complex and automated production processes such as optoelectronics. The significant challenges faced by industrial companies today, such as stricter quality standards, smaller quantities and shorter product life cycles, exacerbate this phenomenon. In this context, digital twins offer a point of reference for improvement by providing an additional database that can be used to make more informed decisions in realtime. The novel contribution of this paper is the design of a simulation as a digital twin in the context of optoelectronic production. It is used to simulate a variety of backlog scenarios in production planning and to provide an additional source of data for backlog control. We also present an application example of how the digital twin can reduce backlogs in the production process. The simulation indicates that the designed model can effectively support the improvement of logistics performance by addressing the significant challenges in modern production.

Keywords

Production Planning and Control; Digital Twin; Simulation; Backlog; Optoelectronic Production

1. Introduction

Digital transformation, combined with increasingly complex production structures and customer logistics requirements, is not new [1]. In this context, achieving high logistics performance while reducing logistics costs is a fundamental objective for manufacturing companies [1–3]. To achieve sustainable advantages in a globalized competitive environment, these companies need to meet all the logistical requirements of their customers. For this reason, transparent analysis of logistics potentials and constraints is highly important [1]. However, this objective is not always feasible, given the complexity and diversity of the processes to be considered within the company's internal supply chain [1,4]. In particular, it is challenging to recognize the correlations between the logistical target variables and the possibilities of controlling them [1,4,5]. Beyond the market's logistical demands, companies must develop new processes to fulfil future requirements. Innovative, automated, and self-optimising production systems are required to meet these challenges. [1,6,7]

Digital twins (DTs) are one way to address these challenges [8]. DTs are a crucial concept in the context of Industry 4.0 [9] and a key driver in the digital transformation of production processes [6,8,10]. A DT can be defined as a virtual replica of a physical object, process, or system [11,12]. It enables realtime monitoring and analysis of the physical counterpart to optimize performance and improve overall efficiency [11–13].

Production planning and control (PPC) allows companies to respond to turbulent market conditions (e.g., maintaining production supply when backlogs occur) [1,14,15]. An efficient PPC system is critical to successfully executing production plans and achieving logistical goals [16].

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This paper aims to present the design of a simulation as a DT in the context of PPC to provide an additional data source for better production backlog control. For this reason, the investigations include a DT at the interface between production and feedback data collection to capture or infer conventionally unavailable information. We are trying to consolidate a database for dynamic adjustments and actions within the PPC. Our paper is based on the theoretical elaboration of Hiller et al.'s [17] conceptual backlog consideration for integrating a DT into the PPC control loop. The remainder of the paper is organized as follows: Section 2 discusses the basics of PPC, the principles of DTs, and how to integrate them into the PPC control loop. Section 3 introduces the use of DTs in optoelectronic production by presenting the real production process and the simulation as a DT. Section 4 presents an application example. Finally, section 5 concludes the paper.

2. Background

2.1 Queuing System in the context of PPC

PPC refers to loading, scheduling, sequencing, monitoring, and controlling the use of resources during production to fulfil production orders [4]. Loading is concerned with how much to do; scheduling is concerned with when to do things; sequencing is concerned with what order to do things; and monitoring and control are concerned with whether activities are going according to plan and corrective actions are needed to fulfil activities within the plan [18]. In this context, Enterprise Resource Planning (ERP) systems perform and coordinate those PPC activities [4,19]. However, ERP systems tend to be cumbersome and do not support the realtime decision-making required in today's market environment [4].

Production planning generally determines the production orders to be processed by scheduling the planned start and finish dates using detailed scheduling [20]. It defines the planned input and output of production and the planned sequence in which orders are processed [1]. Based on the production planning process, production control is responsible for the operational implementation and realization of the production plans. It includes order release, capacity control, and sequence planning [16]. As a continuous progress monitor, production control is used as a cross-cutting task of PPC. This task aims to measure the logistical performance of production processes, identify deviations from the plan, and make recommendations that lead to adjustments to the planned values in subsequent planning iterations. [16] The PPC provides the necessary planning data. The actual data will be collected and provided by DT in the future through the simulation results of this paper.

However, the goals of PPC and controlling can be divided into logistical cost goals (work in process and utilization) and logistics performance objectives (schedule reliability and throughput time), which together represent the economic efficiency of production [1,16,21]. For the remainder of the investigation, the focus of this holistic view will be backlog control in the context of PPC. Production backlog is the difference between actual and planned output ($Backlog(t) = Output_{Actual}(t) – Output_{Planned}(t)$). This control variable can be calculated at any time (t) in production [22,23]. The backlog determines the average schedule deviation of all orders in this system at the time (t) [22]. If the backlog is positive, orders will be completed later on

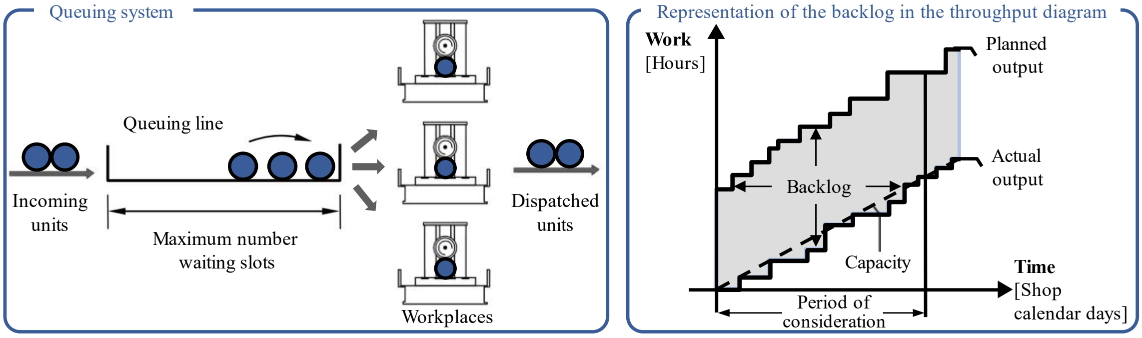

Figure 1: Elements of a queuing model and throughput diagram [1]

average; if the backlog is negative, orders will be completed earlier [22,24]. As a matter of principle, every production process should always be free of backlog [22].

In this context, the so-called queuing model can describe a production system, which allows, among other things, to model the backlog [1,25,26]. The basic concept of the queueing model is shown schematically in Figure 1 on the left. The model deals with processes in which specific units encounter bottlenecks to predict the length of the resulting congestion and waiting times. For example, the goal is to optimize capacity utilization or throughput times [1,26]. Jobs in the queue are postponed until an appropriate resource is available to process the job [1,25,27]. In this way, it is possible to take into account stochastic influences that occur in reality when planning and controlling the production process. The mathematical approach on which this model is based allows us to make the actual sequence of events theoretically understandable and predictable, given known input information about the average arrival and clearance rates of production objects at the work system. In particular, a detailed prediction of correlations between waiting times and queue lengths and the utilization of the considered work system is possible [1], which is highly relevant for backlog control. As shown in Figure 1, the queuing system consists of the queue itself and the individual workstations where the jobs are processed. Three similar workplaces are in charge of processing the orders in the queuing system shown. As soon as one of the workstations finishes processing a job, it starts processing a new job, which is taken from the queue. In simple terms, the ratio of the arrival rate to the dispatch rate can be used to calculate the variables wait time, number of jobs in the system, and utilization [1]. More detailed information can be found in [26].

The throughput diagram is used to further analyze the backlog and queue scheduling analysis. Figure 1 at right shows the basic diagram. The throughput diagram is a logistics model that visualizes processes and process parameters (e.g., output rate, range, work in process) [1,28]. This model is a tool that represents the process parameters in a time-dynamic curve. Apart from this approach, which focuses on the input and output of a working system, the throughput diagram can also be used to analyze the scheduling of the production process. [1,29] In the throughput diagram, the planned and actual output illustrates the schedule situation and, thus, the backlog. The vertical distance corresponds to the backlog in hours. The horizontal distance corresponds to the backlog in shop calendar days (backlog range) [1].

The problem that today's PPC planning systems are sluggish and often do not allow realtime analysis of the production process will be addressed below by developing a concept for DT in PPC.

2.2 Digital Twin: Fundamental principles and twinning in PPC control loop

Over the past 25 years, information technologies have drastically changed industrial production, including new and affordable sensors and virtually unlimited data storage and processing capabilities. In particular, the importance of simulation systems has become increasingly apparent and an integral part of industrial life [30]. The term DT is often used in this context. It's a concept that promises significant efficiency gains in planning and controlling production systems [17,31,32].

The first and widely accepted definition of a DT by Glaessgen and Stargel [13] has recently been adapted to new conditions and republished by many authors as technology has progressed [12,13]. For this reason, a current definition aims to bridge the gap between these partially divergent understandings of DT. By this definition, a DT is a digital representation of a physical system that collects and stores data from the real object in realtime for analysis and optimization [11]. This paper adopts the understanding of DTs according to this definition. In summary, the characteristics of a DT can be described by the terms realtime mirroring, interaction and convergence, and self-evolution [12].

Regarding the transfer of this universal concept to PPC, Negri et al. [31] have shown in research that there are already proven DT approaches in production systems [8,31]. In general, DTs can be used in a supporting role in various applications in the context of PPC. Initial approaches to integrating DTs into PPC have been identified in a literature review (see, for example [33–36]). In these examples, it is clear that they only address an isolated problem in PPC, and that backlog control has not yet been addressed in this context.

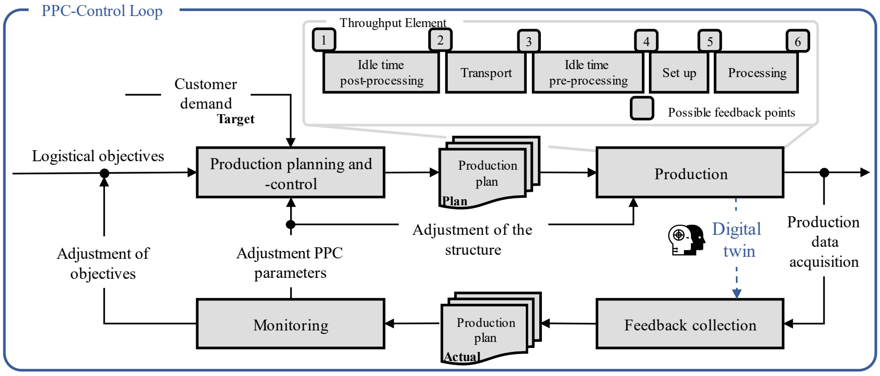

Figure 2: Integration of DTs in the PPC-Control Loop throughput element [17,37,38]

The remainder of this section discusses the integration of a DT into the PPC control loop. The PPC control loop shown in Figure 2 illustrates the control task that manufacturing companies must master to achieve their logistics goals [12]. Based on a company's objectives (e.g., performance targets) and customer requirements (e.g., quantity and timing), which represent the target values, the control loop systematizes the planning of production schedules (plan) and the control of processes during production. Furthermore, the PPC control loop represents the generation of production data based on operating and machine data. This feedback data is used as actual data to calculate deviations from the plan and thus for production control to derive improvement actions and increase target achievement. [38] The purpose of this comparison is to continuously check whether the target or plan values are being met, which is done successively using monitoring. If deviations are detected, they must be analyzed, and measures proposed and implemented. [1,38] Recording actual data requires time evaluation of the production process. In today's production, discrete time stamps are the most common form of time evaluation [20,38]. Figure 2 illustrates points where feedback data can be extracted from the production process as a throughput element. The data is typically generated digitally based on RFID technologies [38,39].

As seen in Figure 2, it is helpful to integrate the DT at the interface of production and data collection to perform realtime analysis that enables adjustments based on the plan and target data. In addition to the discrete time stamp data acquisition described, using DTs in production also provides the ability to simulate and analyze the production system virtually [8,40–42]. The literature suggests that information from realtime simulation, such as the actual progress of a production process, should be continuously accessible and evaluable to the PPC to analyze and organize the production process more transparently [17,43,44]. Using realtime data makes decisions faster, allowing adjustments to be made earlier and more efficiently. Realtime simulation can also provide continuous data for PPC control when using DTs in production. [17] This concept is discussed in the following chapter in the context of optoelectronic production.

3. Architecture of a simulation model in optoelectronic production

3.1 Real model: Optoelectronic production

The production of optoelectronic components is a highly complex, multi-stage process that requires exceptional support from modern technologies due to its high demands on quality. In addition to the generally high customer demands regarding timely delivery and quality requirements, manufacturers must develop new practices to meet market expectations. [45–49] On the one hand, new production technologies such as adaptive polishing [50] and two-photon polymerization [51] need to be embedded in the process chains to produce high volumes with high precision. On the other hand, digital technologies such as DTs are of great importance for this industrial sector, as they promise to increase quality and efficiency simultaneously. From a logistics perspective, this means that manufacturers in this sector must deal with high uncertainty about their capacities [50]. The associated planning uncertainties are, for example, due to variable production parameters, high-quality requirements, and rework in the production process [45,50].

The production process is described below to define the real twin for the following elaborations in the simulation context: Sand is the starting material for optoelectronic production. It is used to produce silicon. To obtain silicon wafers, molten silicon is pulled into a monocrystal. The monocrystal is then cut into silicon wafers less than 1 mm thick. [45,52] This step will not be detailed in the simulation, as this product is a purchased part. The first step to be considered is the polishing of the silicon wafer. This step significantly impacts the quality of the product, as polishing has a major effect on the mean roughness value, which is used in practice as a key quality indicator [45,52]. This is followed by the lithography process, which defines the structure of the wafer plate. For this purpose, the base plate is coated with a photoresist layer susceptible to light. The structure of the mask is then transferred to the material by exposure. [45,53] The light changes the chemical composition of the previously applied coating. The exposed parts of the coating are soluble and are removed in the manufacturing process. A subsequent etching process creates the resist structure on the wafer plate. A copper filling is then introduced into the etched structure as a conductive interconnect, and excess material is removed by polishing. This process is repeated several times until a three-dimensional chip structure is created. [52,54,55] The last production step is contacting the chip with an electrode. [52,56] These steps represent the production process to be simulated and, thus, the real twin.

The real twin serves as a reference process for the simulation where the required data is collected. This data is used in DT to run the simulation, analyze the collected data, and vary the parameters required to simulate the properties before the resulting parameters are reflected to the real twin.

3.2 Simulation model development design decisions

Based on the definition of a conceptual model in Robinson (2015) [57], this section formally describes the architecture of the DT to be simulated. The description shows the software independent structure and forms the basis for the simulation. The conceptual model of the simulation is based on different modules, which

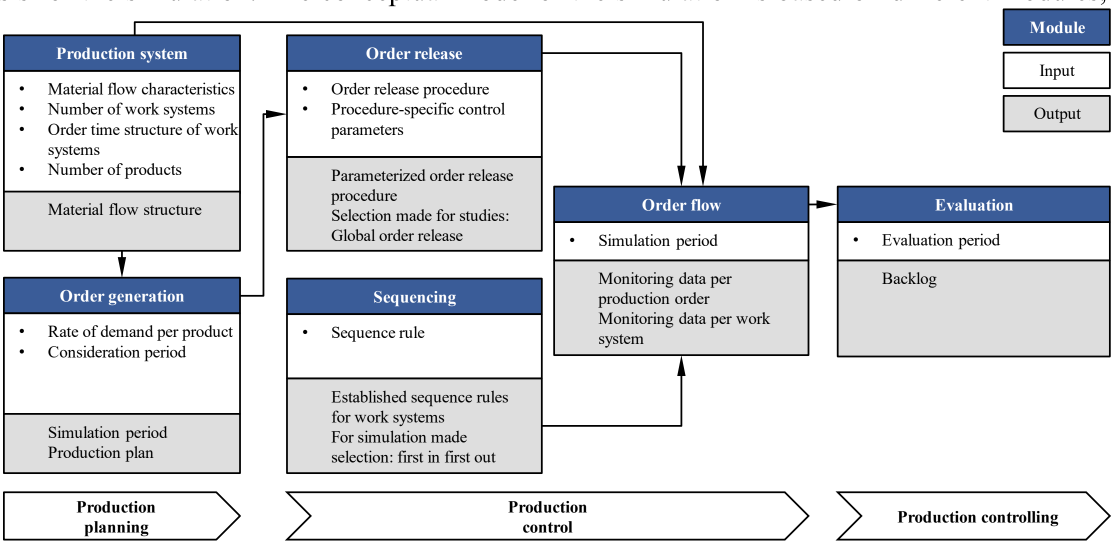

Figure 3: Schematic structure of the simulation as a conceptual model [57]

are assigned to the tasks of production planning, control and controlling. In the chosen representation, the inputs describe the experimental factors that are changed to run the simulation. The outputs are the reports that describe what state has occurred in the context of the simulation. The schematic structure of the simulation model is shown in Figure 3.

In production planning, the production system is defined by the material flow, the number of work systems, the order time structure, and the number of products. The module is used to output the structure of the material flow. In addition to this module, order generation is schematically structured in the context of production planning. For a complete description of order release, sequencing, and order flow in production control, see Figure 3. Based on the input and output information from production planning and control, the simulation is run for a specified simulation period. In the process, feedback data is generated for each work system. The production controlling module then evaluates the data concerning the backlog.

3.3 Simulation architecture of the digital model and its implementation

The digital model presented below must be permanently synchronized with the real system to reproduce the dynamic behaviour. Synchronization aligns the real production system and the digital model [58,59]. Once the initial digital model is synchronized, it can evaluate performance and optimize services. These functions allow a bi-directional flow of information [60]. The simulation of the DT of the production process was created based on the software Plant Simulation from Siemens. Specific customer orders trigger the process pulled through the production process by a pull control implemented by a method in Plant Simulation. The production orders are released globally based on this methodology. Following the production process, the initial polishing and the individual steps of the lithography process are performed, which in the simulation are carried out by individual workstations. An input/output control system centrally coordinates both workstations. For this purpose, the default methods programming environment was used in the settings of the workstations in Plant Simulation. After these two steps, detailed quality control is performed. This step plays a central role in the simulation because the quality characteristics of the wafer plates significantly impact the products' functionality. In the simulation, three products (BEs) are represented, which differ in product characteristics via quality. The customers' orders always refer to one of the three product qualities. Following the queue model, the wafer plates are contacted with the electrodes. The electrode is provided by a second source and considered a purchased part in the simulation. The queue's capacity is dimensioned in the simulation with three waiting slots. A product-dependent perturbation is implemented in the assembly step to simulate the quality-dependent factors described above (e.g., changing production parameters and reworking). Specifically, for all products of Quality 1 (low), an availability of 80% of the machine was randomly distributed over the simulation time, and a Mean Time to Repair (MTTR) of 10 minutes was assumed. For Quality 2 (medium) and Quality 3 (high) products, the availability is 75%. The MTTR is also 10 minutes in both cases. In addition, an open database connectivity interface is embedded to access external databases. The simulation results are transferred via a single-tier driver to a Microsoft Excel data source, which can be analyzed and transferred to the real twin.

In summary, the DT provides insight into optoelectronic production and a more detailed picture of the current performance of systems. This data can be used to make analyses more transparent and to detect

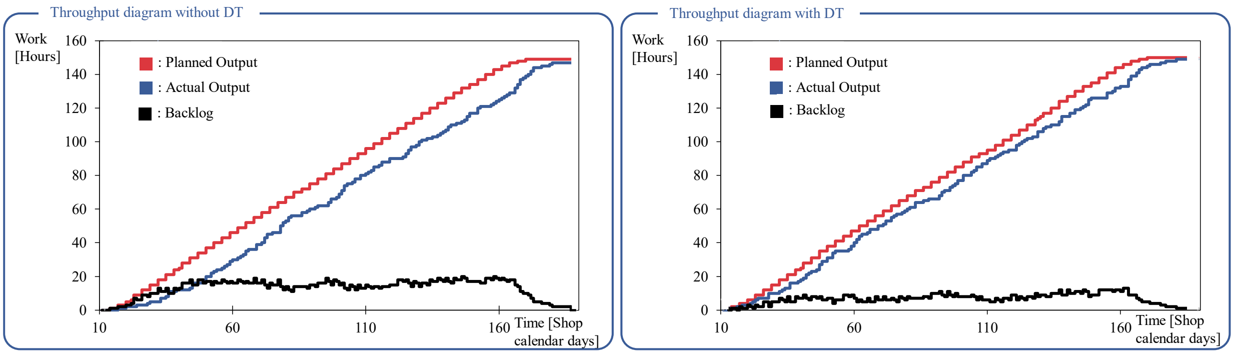

Figure 4: Simulation results as a throughput diagram

deviations from plan earlier. This provides additional information for timely corrective action. The results of a case study that demonstrates the benefits of simulation as a DT are presented in the following chapter.

4. Example of application – Potentials of simulation as a digital twin

This section aims to provide a detailed insight into simulation in the form of an example. The following shows how DTs can help improve the efficiency of implementing production control measures in the optoelectronic production process. As a concrete example for this consideration, backlog control in the production system was chosen. The DT captures the actual output in the simulation. Production planning explicitly specifies the planned output. Two scenarios were compared to demonstrate the benefit of the DT for backlog control in the example. Both are shown in Figure 4 in a throughput diagram to visually illustrate the positive effect of using a DT. The "conventional" scenario is on the left, where production runs without DT. In this case, response times are slow [17], and adjustments are often delayed, for example, when production parameters need to be adjusted or when quality problems occur [52]. The figure on the right shows the scenario where a DT supports production. DT support was simulated to the extent that an additional database was created to identify backlogs in the production process earlier and to adjust production capacity promptly. This additional database was made possible by continuously retrieving quality and progress data.

Figure 4 clearly shows the deviation between planned and actual output, combined and represented by the backlog. Ideally, the planned and actual output curves should be aligned, as the backlog would be zero according to the above equation. However, as can be seen, the ideal case is not present in both scenarios, as there is always a positive backlog during the production process. Based on the formula presented, we can see that the orders have a positive average backlog and, consequently, a time lag concerning the planned dates. However, comparing the two scenarios indicates that the backlog is lower on average in the case of support by a DT. Nevertheless, in the case of DT support, the backlog cannot be eliminated due to the implementation of a simulative manipulation of machine availability and a mean time to repair. The reduction of the backlog to zero towards the end of the simulation is because only a limited number of

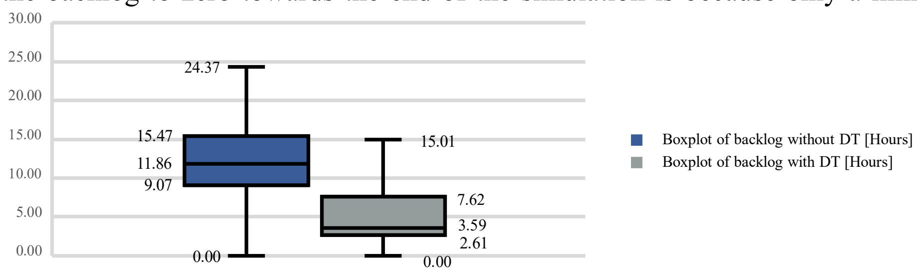

Figure 5: Boxplots of backlog with and without DT

orders were released, and the simulation continued until all orders had been processed. The parallel course of the planned and actual output curves indicates that the backlog could not have been cleared if more orders had been released. In addition, the parallel development of the two curves suggests that the backlog cannot be reduced without a capacity increase. Therefore, specific measures must be taken to adjust capacity in the short and medium term until the accumulated backlog is cleared [61].

In addition, the throughput diagram suggests that the scatter of the backlog is smaller due to the DT, as the actual output fluctuates less. As in the previous argument, this reduction in variability can be explained by the expanded and more transparent database. Additionally, the figure shows that the backlog range (horizontal distance between planned and actual output) is lower when using a DT. This reduction indicates that less time has to be invested in reducing the backlog in production with current capacity. This effect is an excellent description of the added value that DT has created in this application example. To examine this aspect in more detail and to demonstrate the added value of DT, a statistical analysis of the simulation results was performed using box plots, as shown in Figure 5. The previously inferred finding that the mean backlog and the scatter are on average lower when a DT is used is confirmed by these investigations. The simulation results show that support from a DT reduces the median from 11.86 hours to 3.59 hours. In this case, the location parameter characteristically shows that the spread has a much smaller backlog as the median is closer to zero. Thus, this measure provided a central tendency and was deliberately chosen for this application example because it is insensitive to outliers.

Comparing the two scenarios, the same interpretation can be made for the upper and lower quantiles. As shown in Figure 5, the box's height is smaller when a DT is used, and apart from the outliers, the minimum and maximum values of both data sets have a smaller range. The interquartile range (height of the box) can be interpreted as the mean 50% of the values being 1.39 hours ((15.47 hours - 9.07 hours) - (7.62 hours - 2.61 hours)) closer together when a DT is used. In terms of the minimum and maximum value, it can be said that the backlog varies by 9.36 hours less when a DT is used. Based on the findings that the box's height is smaller, the outliers have a smaller spread, and the simulation data reveal a lower median, the statement previously made based on the throughput diagram can be confirmed that the backlog is smaller on average and has a smaller scatter when a DT is used.

In terms of applications, these results were simulated by continuously recording and mirroring the actual data. The reduction of the median and the two quantiles of the backlog in Figure 5 is due to a depreciation of the idle times of the individual workstations in the production process. The reduction is caused by the additional database, as described above. The decrease in scatters is due to better coordination of production orders in general, a better adaptation of process control to changing production parameters, and early assurance of quality requirements. On the one hand, this example demonstrated the added value of simulation as a DT for PPC in general. On the other hand, the simulation presented in Section 3 could be practically applied and checked for plausibility.

5. Concluding remarks

The overall objective of our work is to present the design of our simulation model as a DT in the context of PPC to provide an additional source of information for backlog control. Initially, an overview of production control was given to communicate it comprehensibly. Then, the concept of a DT, which is crucial for this paper, was introduced, and its possible integration into the PPC control loop was shown. Finally, the conceptual model and simulation results were presented and demonstrated by an application example. Our results suggest that DTs in production can help to organize production control and monitoring tasks more efficiently. Thus, this approach can address and mitigate today's sluggish PPC systems, high-quality requirements, and global competitive pressures described in the introduction. The demonstrated benefits of DT are primarily due to the additional data generated. This provides an information advantage, as quality and progress data can be continuously retrieved in the production process to expand the discrete database. Ultimately, the DT simulation result provides an approach to improve the economics of manufacturing from a logistics perspective, as it has the potential to improve performance and reduce costs. More specifically, in practical application in the production process, the DT will provide detailed information in realtime, enabling the effects described above through a response advantage.

For practical applications in industry, the simulation model has the advantage that adjustments to the production process can be made much more quickly, resulting in better key figures. Evaluating the identified potentials based on simulations with further experimental or industrial datasets is necessary. Finally, it is essential to note that future research should focus on other PPC tasks besides backlog control and on how this additional information can be used to improve production control and monitoring.

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Biography

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