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Exploring The Potential Of Digital Twins For Production Control & Monitoring

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Abstract

The achievement of a high level of logistical performance is a primary goal of manufacturing companies. In order to remain competitive, companies must constantly improve order processing to ensure short delivery times and high delivery reliability. Production planning and control is a core function of manufacturing companies and is responsible for routing production orders through the stations involved in order processing such as procurement, production and dispatch. Yet managing production efficiently and achieving a high logistical performance remains a genuine issue, even with increasingly digitalized and automated processes. The concept of the digital twin promises an improved database to enable companies to reach more informed decisions. As yet, the potential for utilizing this database has not been thoroughly explored in the context of a constant measurement of the backlog and output. In addition, there are various divergent definitions and approaches to the application of digital twins. This paper discusses the potentials of the different tasks of production control and monitoring in relation to the acquisition of dynamic data in real-time. A method is provided that continuously calculates the backlog and output. Furthermore, an example of application is presented that shows how this information can be used for production control. Our results indicate that by exploiting this information, logistic performance can be improved.

Keywords

Production planning & control; Logistical KPIs; Digital twins; Production logistic models

1. Introduction

Beside production costs and quality, logistical performance such as a short delivery times play a central role for companies to compete in today's economy [1,2]. In an increasingly dynamic and unpredictable market environment [3], companies are constantly searching for new approaches regarding digitization trends to satisfy customer requirements. The digital twin (DT) is a central concept associated with Industry 4.0 and a crucial factor for the digital transformation of factories [4,5]. A DT can be generally described as a digital information construct of a real system [4]. As definitions vary, a DT is most often characterized as a simulation of a physical product or system, or a model of a system that can be used for subsequent analyses [6]. The applications of DTs are studied in different scientific disciplines. In production engineering, the approaches have the common goal to improve competitiveness, efficiency and productivity of production processes [4]. In this context, various fields of application can be identified, such as the simulation of the product itself or production processes, product life cycle management, product development and design as well as planning and decision support [4,6,7].

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With the help of production planning and control (PPC), companies can respond to the turbulent market conditions for example maintaining the production supply through specific adjustments in the inventory management [8]. Production planning defines individual production processes in terms of schedules, capacities and quantities [9]. Production control is responsible for the actual implementation of production plans as well as handling unavoidable disturbances in production [10]. Eventually, an efficient and accurately structured production control and monitoring system is crucial to successfully execute production plans and consequently to meet logistical as well as economical company objectives [11].

In the field of PPC, several research applications of DTs can be identified such as the simulation of processes in order to detect production errors [12], simulation of production lines [13], prediction of throughput times [14] and conceptual work on real-time data acquisition capability [15]. In order to take full advantage of the potential of DTs in this context, existing models of production logistics (see e.g. [11,16]), which allow the simple and accurate description of the logistic behaviour of production systems, could be used to leverage the benefits of DTs in terms of a simplified evaluation of data. A potential approach is the measurement of output and backlog in real-time. However, adjustments regarding the real-time data acquisition are missing in current models. Having filled this gap, production logistic models can help to provide an improved information base for deriving decisions, such as capacity management measures.

The paper is organized as follows: First, we give an overview of the fundamentals of production control & monitoring as well as logistic parameters such as backlog. Secondly, we illustrate different concepts of DTs and define the data input needed for constant backlog and output tracking. Finally, we present a model approach for tracking backlog and output and examine the resulting potential in the area of production control and monitoring.

2. Fundamentals of production control & monitoring

The 'Model of Production Control' developed by Lödding (adapted by [17]) specifies the tasks and interdependencies of production control (cf. Figure 1). In addition, a linkage of logistic objectives and the different tasks of production control is provided by modelling control and actuating variables. [11]

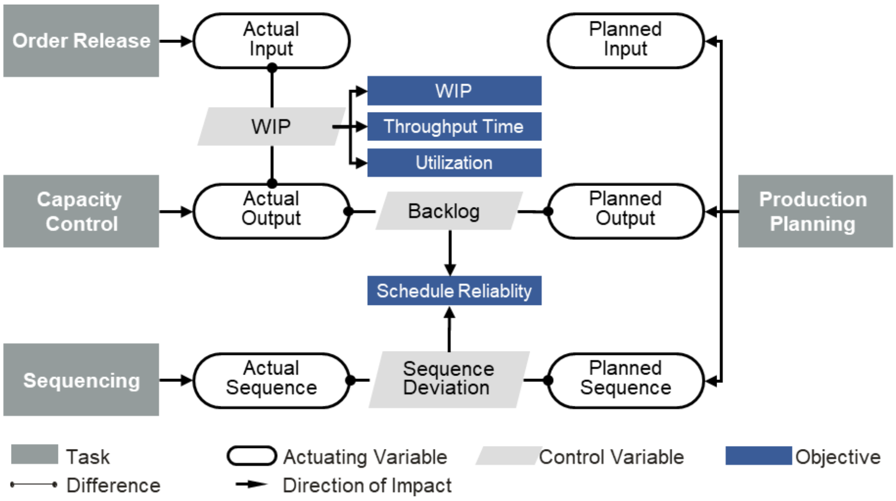

Figure 1: Model of Production Control [11,17]

Production planning defines the production orders to be processed by scheduling planned start and finish dates using detailed scheduling [17]. Hence, it defines the planned input and the planned output of production as well as the planned sequence in which the orders are to be processed. Production control is responsible for the operative implementation and realisation of the production schedules. It comprises order release, capacity control and sequencing [11]. Starting from the production plan, order release controls the dispatch of orders to production. Consequently, it determines the actual input of the production. Capacity control defines the actual output of production as it determines in the short term about the actual use of capacities, such as working time and the assignment of employees with multiple qualifications to machines [11]. An important procedure is backlog control. The backlog is shown by a comparison of actual output with the planning targets (planned output) of a capacity unit. A comparison of the actual input and output results in the Work-in-Process (WIP). Sequencing determines the actual sequence in which jobs are processed. By comparing the actual and planned sequence, it is possible to assess the schedule reliability. [11]

Production monitoring or controlling is a cross-sectional task of PPC that is also called PPC-Monitoring. PPC-Monitoring aims to measure the logistical performance of production processes, identifies deviations from plan and provides solutions. Data basis for the PPC-Monitoring is plan data as well as production feedback data. [11]

According to Wiendahl, there are four logistic objectives in production: WIP, throughput time, utilization and schedule reliability (cf. Figure 1). [10] The objectives can subdivided in targets of logistical costs (WIP & utilization) as well as performance (schedule reliability & throughput time) [10]. Order throughput time defines the time between order release and the end of a processed order. The end of a current operation and the end of the previous operation defines the throughput time of a single work process. Schedule reliability is defined as the percentage of production orders closed within a predefined tolerance. [11] Typically, short throughput times combined with high schedule reliability are targeted [16]. The WIP describes the quantity of material or orders that is tied up in the individual stages of production through released orders. WIP affects the costs of a company in the form of capital commitment. [11] Utilisation describes the ratio of average and maximum possible performance of a work system [16] and is traditionally maximized, especially when expensive equipment is involved. However, too high utilization can lead to increased WIP and throughput time [11]. As Schmidt and Schäfers state, the objectives have contradictory dependencies, so that a parallel optimization is not feasible. Companies must therefore consciously consider positioning their production activities in areas of tension that arise from opposing logistic objectives. [18] Models of production logistics like the Logistic Operation Curves by Nyhuis are able to provide decision support [16]. Production logistic models are generally used to understand the prevailing situation and the dynamic behaviour of a system, to discover the root causes of problems and their effects, or to determine an information base for the derivation of measures [16].

3. Digital twins

3.1 Basic principles of digital twins

The first and widely accepted concept and definition of DTs was provided by Glaessgen and Stargel from NASA. This approach involved monitoring aircrafts by combining system status monitoring with sensor data, maintenance histories and other fleet data in order to assess the current status but also allow forecasts about the technical condition of the vehicle.[19] Glaessegen and Stargel, with additions by Tao et al., provide the following basic definition of DTs: "A digital twin is an integrated multi-physics, multi-scale, probabilistic simulation of a complex product and uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin" [19,20].

The concept of using a comprehensive digital image of a system or product to run simulations in real-time was adapted and transferred to a wide range of research areas. In a comprehensive review, Negri et al. show that divergent approaches and understandings of DTs in the field of manufacturing systems exist. According to their findings, a DT mostly represents a simulation of a product/ system or a model of a system, that can be used for different types of simulations. [6] As the definitions and applications of DTs differ through disciplines, the concept of DTs can also vary in terms of the level of data integration. Referring to this, Kritzinger et al. (see [4]) distinguish between the terms digital twin (DT), digital shadows (DS) and digital models (DM). The authors state, a DT includes automatic data flow from the digital object to the real object and vice versa. Whereas DS include only a semi-automatic flow (physical to digital object) and DM comprise solely a manual data flow [4]. The mentioned relationships are illustrated in figure 2.

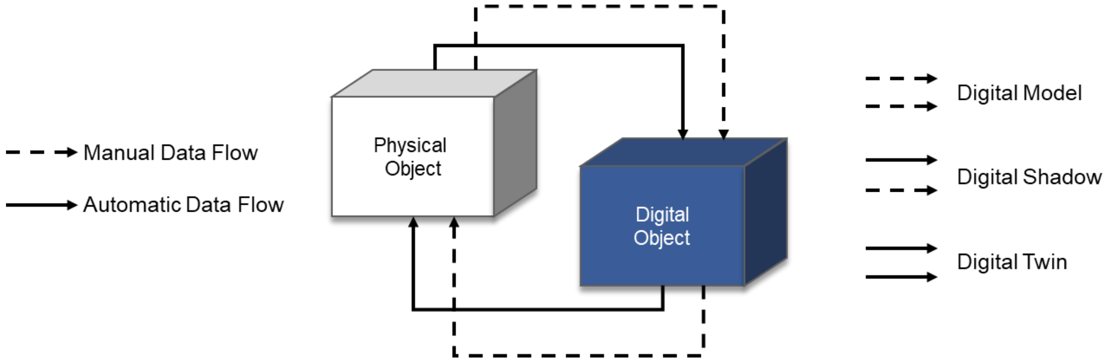

Figure 2: Concept of the DTs in terms of the data flow (based on [4])

Possible uses along the smart manufacturing environment can be divided in three areas: (1) support of condition analyses and maintenance such as monitoring cracks in the physical twin, (2) an accurately digital image of the physical twin e.g. along the product lifecycle or in the production process as well as observing time behaviour and (3) DTs providing decision support through extensive analyses of product or production systems [6].

Regarding PPC, DTs can be used in a wide range of applications. In literature, it is generally possible to distinguish between concepts for embedding DTs into production systems/ PPC or case studies in which application examples are presented and in each of these, different key areas of the PPC are highlighted. On the conceptual level, Schuh et al. refer to DTs as a complete, comprehensive representation of the production system, hardly feasible e.g. due to heterogeneous data sources. Thus, the concept of the digital shadow is presented, which envisions considering only a subset of the data, namely those necessary to clarify the issue at hand. [21] Uhlemann et al. demonstrate the potential of real-time data acquisition and subsequent processing in a DT-supported production environment. For this purpose a concept of a learning factory is developed [5]. Denkena et al. present an approach on how to generate a DT efficiently by using scans and object recognition as well as company-specific data with focus on creating a simulation model. [22] In another conceptual integration, Yang et al. discuss a simulation approach in which a PPC system is set up in a way that production processes are visualized, key performance indicators are compared and PPC parameters are optimized to react on several uncertainties like quality issues [23]. Boschert et. al present a concept based on linking different DTs (e.g. of the production system, product in use or system in use) to a value network. For example, a DT during the operational phase enables fault identification by linking physics-based simulation with live data [24].

At a more detailed and specific level, procedural approaches and case studies can be found. Korth et al. developed an integration of a discrete event simulation into a digital twin architecture for real-time simulation (e.g., prediction of order times or production disruptions) for decision support [13]. Vachálek et al. are modifying production parameters in order to monitor the behaviour of the production system and optimize the production plan [25]. In addition, Sun et al. use a DT of an assembly line to predict and optimize throughput times [14]. Reviewing the given literature on DTs in the field of PPC, it is apparent that mainly conceptual (technical) concepts and procedural approaches are discussed. Model-based decision support systems for the simplified evaluation of data as well as illustration could not be identified.

To conclude, a DT represents in the following a real-time simulation of the production process or of the processed product itself (see e.g. [12]). We assume that data such as progress and quality can be continuously retrieved from running processes, so that (model-based) analyses for PPC purposes do not depend solely on discrete feedback data.

3.2 Digital twin integration into the PPC control loop

The PPC control loop illustrates the control task that manufacturing companies have to address with regard to the achievement of logistical goals. Based on a company's strategic objectives and customer requirements (target), the control loop systematizes the planning of production plans (plan) and the control of processes during production. Furthermore, the control loop includes the recording of production data within the scope of the operating and machine data logging (actual). [9] Compliance with the target and planned values is to be continuously checked by monitoring through a comparison with the recorded actual data. Identified deviations must be analysed, measures proposed, implemented and monitored. Possible measures are the adjustment of the objectives, a change of the PPC parameters such as WIP level or a reconfiguration of the PPC procedures, an adjustment of the production structure as well as the organization or short-term measures (production control). [16,9]

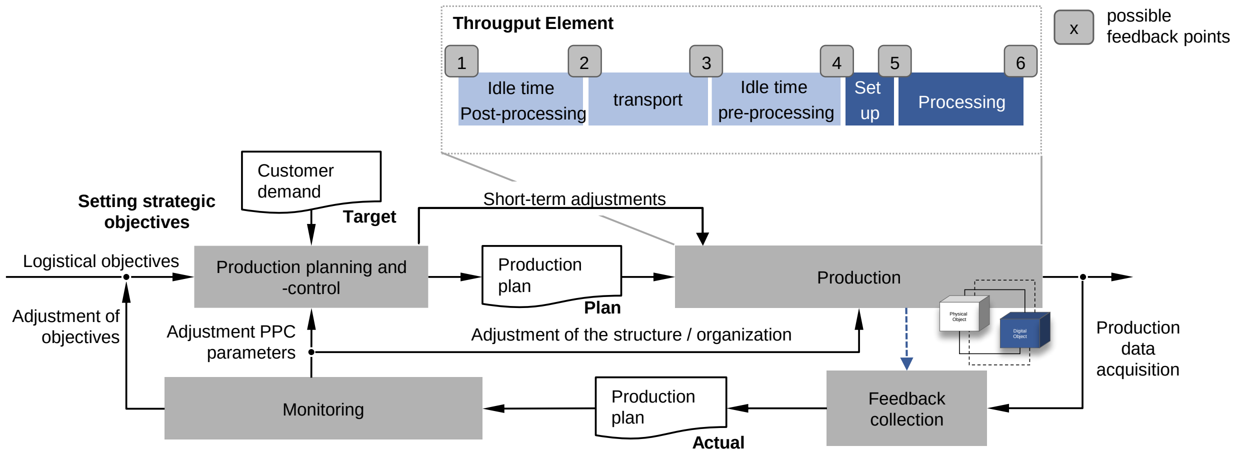

Figure 3: Integration of DTs in the PPC-Control Loop (based on [9]) throughput element (based on [18])

To generate production feedback data (actual data), it is necessary to assess the temporal sequence of production processes. This can be done by collecting discrete time stamps. Figure 3 also displays (upper right corner) the throughput element of a production unit (e.g. of a single operation). The throughput element contains the components of the throughput time: inter-operation time (idle-time post- & pre-processing, transport) and operation time (set-up & processing). [17] Collecting time stamps at the marked feedback points (1-6) allows the discrete assessment of the components of throughput time and, taking into account planning data, the tracking of logistic objectives (cf. chapter 2). For instance, if a production system is designed to measure only point 4 and 6, it is not possible to measure set up time or transport time. However, it is important to state, that the acquisition of each feedback point generates expenditure and must therefore be carefully evaluated [17]. It can be stated, though, that the collection of a large database increases the transparency of production [17].

The use of DTs in production provide the capability to simulate and analyse the production system, as well as its logistical features, and allows a detailed visualization of the manufacturing process from individual components to the entire assembly (see e.g. [4]). The potential influence of the generated information was added in this representation of the control loop, which simply involves a direct connection of production to feedback collection. We propose that information of the simulation, such as the actual production progress of a single production process, the actual output or certain product characteristics, is extractable and usable for the PPC continuously. Most common data acquisition methods in terms of recording production feedback data are able to collect timestamps at certain feedback points. The granularity is reflected in the frequency of feedback. Partial feedbacks, e.g. from individual assemblies within processing, are possible to increase accuracy. Besides recording data manually, barcodes and QR-Codes are the most used technologies [26]. Considering the use of DTs in production, continuous data, e.g. from process simulations, can be acquired in real-time in addition to the usual discrete data acquisition methods and enrich the available information in the PPC. By using real-time data, decisions can be made more promptly, for example, in order to apply capacity management measures more efficiently. Production logistic models can help to provide an information basis for these decisions. However, an adaptation to continuous data is missing, which will be presented in the following.

4. Exploring the potential of digital twins for manufacturing control & monitoring

Evaluation of the potential data provided by the application of DTs allows existing logistical description models to be extended. As outlined above, we presume that by continuously simulating the production process, it is possible to continuously record the output, deviations from the planned process and product characteristics. Following considerations are based on the representation of the backlog in the throughput diagram (see [11]). In general, throughput diagrams can be used to describe dynamic system behaviour (see e.g. [16]). In order to depict the backlog, lateness and output rate of a system, it is necessary to model the actual and planned output [11].

4.1 Model for constant tracking of backlog and output

The output respectively progress of an ongoing operation can be measured in work completed (in hours) [16]. As in figure 3 illustrated, there are two time stamps to assess the temporal sequence of the operation time. The start of set up and the end of an operation can be captured. Often the actual operating time differs from planning data and thus backlog occurs. This may be caused by a lower mean output rate (e.g. due to machine failures) or faulty scheduling [27] and results in the planned output not being achieved. The standard measurement accuracy consists of measuring the end respectively the start of processing and comparing the actual processing time (operation time) with the planning data. However, the resulting backlog or lateness can only systematically be registered at the end of processing (time stamp 6). By implementing DTs, a simulation of the production process is created, which could allow a sharper level of detail to be captured and significant backlogs or lateness could be detected while processing. This concept is visualized in Figure 4. It illustrates a progress (planned, actual) of work completed of a single operation over time (in shop calendar days [SCD]). In this figure, it has been assumed for simplification purposes that no backlog existed at the beginning of the assessment period.

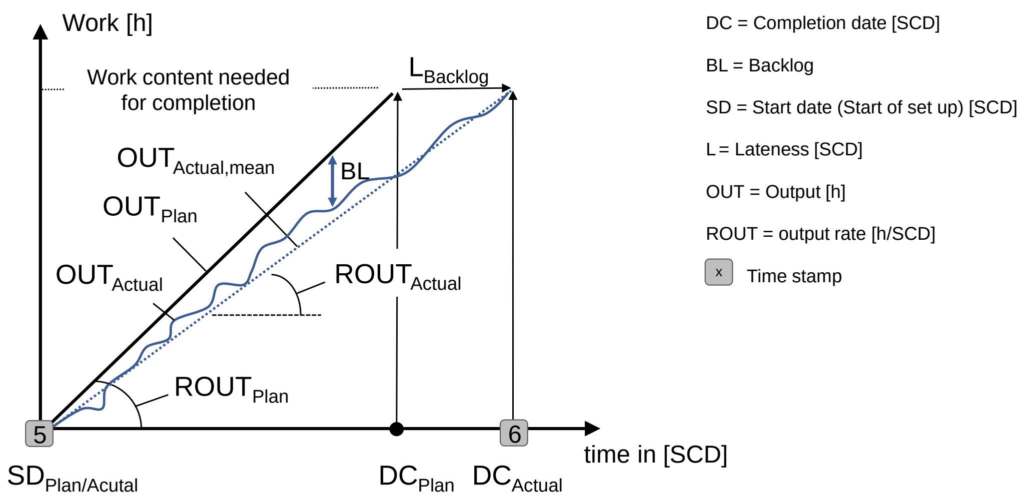

Figure 4: Degree of progress in the operation flow with reduced output rate

The illustration contains three curves that show the output of a production unit as a function of time in shop calendar days. The planned output OUT_{Plan} in hours describes the planned course of processing. It reaches the work content needed for finishing the processing at the planned completion date. The gradient of the line shows the planned mean output rate $ROUT_{Plan}$. Further, the illustration shows the actual output OUT_{Actual}

that could be obtained from the DT. $ROUT_{Actual}$ can be determined by taking the gradient of $OUT_{Actual,mean}$ (mean actual output) into account. It can be seen (exemplary), that $ROUT_{Actual}$ is lower as planned. This implies that less work was completed in the same time than planned. This results in the backlog of a single operation BL_{OP}, which can be derived from the vertical distance from the OUT_{Actual} and OUT_{Plan}. BL_{OP} can be calculated at any time by

$$OUT_{Plan}(t) - OUT_{Actual}(t) = BL_{OP}(t) \qquad (1)$$

Similarly, the current lateness of processing through backlog $L_{Backlog}$ can be assessed at any time by the horizontal distance between OUT_{Plan} and OUT_{Actual}. $L_{Backlog}$ at completion date of a specific operation can be calculated taking into account the planned and actual completion time. In case of discrepancies in the process, discrete data acquisition methods would assess the backlog at the actual completion date. In case of very long processing times significant backlogs would possibly be detected late. This can lead to further logistical difficulties in the production system.

4.2 Derivation of potentials

Based on the model presented, measures can be derived to ensure logistical efficiency. In the following, potentials are identified for the tasks presented in chapter 2.

Capacity control is critical for ensuring a high level of schedule reliability [11]. Backlog control is part of the task capacity control. The underlying principle of backlog control is to adjust capacities at the short term so that production reaches the planned output despite disruptions. Key aspects of backlog control are the measurement of backlog and the selection of measures for capacity adjustment.[11] The aim of backlog control is to eliminate backlogs and thus schedule deviations as quickly as possible in order to meet the deadlines of external or internal customers [28]. The utilization of DTs could enable production controllers to measure the backlog more accurately and in shorter time spans (in comparison with discrete methods). An earlier identification allows a prompt initiation of measures and thus an earlier reduction of the backlog. By initiating measures more promptly, very high backlogs can be potentially avoided. This issue is addressed in the example of application in chapter 5. It must be noted though, that in case of inaccurate estimated working contents or a strongly volatile output rate, the evaluation of BL_{OP} can lead to uncertainties, as a high backlog could occur only partially in the process.

Order release describes the task in production control that determines the point in time from which production may process an order. There are different trigger logics for the release of production orders, namely periodic and event-orientated. In case of an event-orientated logic, production orders are released when a specific event appears such as falling below a certain WIP level. [11] An improved overview of the production processes by DTs can enable order release to make more informed decisions. For example, if a significant deviation between planned and actual progress in a work system is detected, the order release can react by releasing orders later. Thus high queuing times can be avoided. Methods for order release such as the “Load oriented order release” [11] could be applied more efficiently.

In the context of PPC-Monitoring, the utilization of DTs can improve the quality of production feedback data by enabling, as shown, automated and more detailed data collection. In PPC-Monitoring, it is crucial not only to measure logistic objectives such as poor schedule reliability, but also to identify underlying causes such as high backlogs at specific workstations or an unpunctual order release [27]. The model presented could facilitate an up-to-the-minute overview of operations, as well as the display of lateness and backlogs. For PPC-Monitoring, this essentially provides an information advantage with regard to the management of these disruptions, as necessary measures can be adopted earlier. By also retrieving product characteristics, production errors such as geometrical deviations could be detected earlier in the process (e.g. [12]). For production technicians, this implies the possibility to influence the accuracy of the production process (see also [12]). For production control and monitoring, it offers an information advantage in order to systematically counteract production errors. If, for example, it is known within the process that a certain quality level is not reached, appropriate reworking measures can be scheduled in earlier.

Furthermore, based on insights gained in monitoring, information could be mirrored to other parts of the PPC, such as order management or procurement. Possible applications in order management are the dynamic calculation of delivery times, dynamic pricing or a more efficient management of supply processes (see [29]).

5. Example of application – Potentials of digital twins in the optoelectronic production

The potentials described above are now illustrated with reference to a production system for manufacturing optoelectronic components. Manufacturing optoelectronic components is a highly complex multi-step process often requiring extensive manual labour and operational effort. The major trends in the production of optoelectronic systems include the functional integration and miniaturization. In addition to the generally high customer requirements in terms of on-time delivery, manufactures in that specific industry need to develop new processes in order to meet the market expectations. Production technologies such as adaptive polishing [30] and two-photon polymerization [31] need to be integrated in process chains so that high volumes can be produced in an advanced level of precision (sub-wavelength range). This leads to the point, that manufactures in the optoelectronic industry have to deal with high level of uncertainty regards their capacities due to e.g. changeable production parameters, high quality requirements, rework and ultimately a high range of process times [30]. As mentioned earlier, in case of long processing times significant backlogs can be detected late by using discrete measurement methods. Positive mean backlogs directly result into schedule deviation [32,27]. In the following it is presented how DTs can help to improve the efficiency of the implementation of production control measures in a production system for optoelectronic components by being able to display delays in the process early. It is postulated that the production process is simulated and the data needed for the proposed model is available.

As stated, capacity control is crucial to achieve a high schedule reliability. Short-term capacity measures are, for example, the use of overtime respectively the reduction or an internal exchange of workers [11]. The connection between the response time and minimum installation times of capacity measures can be visualized with the help of the capacity envelope curves (see [28]). The envelopes reflect the capability of a production system to respond to capacity changes. [28]

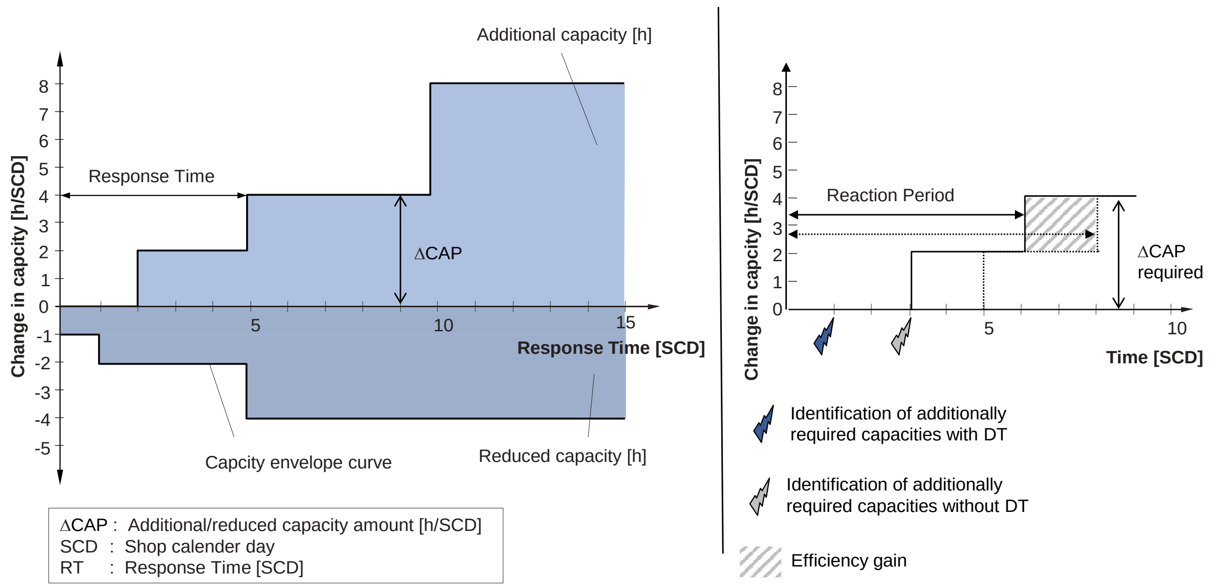

Figure 5: Capacity envelope curves (based on [28])

The left part of figure 5 shows the general capability of the production system (e.g. two-photon polymerization) to react on changes in capacity requirements. The area above the x-axis represents the additional capacity that can be provided and the area below the x-axis represents the capability to reduce capacity [28]. In this example, the installation of additional capacity of 4 hour per SCD (ΔCAP), will require 5 days from the time of initiation. This can be described as the (technical) response time, e.g. to organize extra shifts.

DTs enable an insight view of production processes and a more granular picture of the current output of production systems. As illustrated in chapter 4, by utilizing this data with the help of production logistic models, backlogs could be detected significantly earlier. Thus, an additional data basis can be created so that capacity control measures can be initiated promptly. This is shown in figure 5 on the right hand side. Again, in this example the (technical) response time of installing an additonal capacity of 4 hours per SCD is 5 SCD. As previously pointed out, there is a risk that backlogs may be detected late among processes with long processing times. Utilizing DTs can help to reduce the reaction period of capacity measures. The reaction period of enabling a measure consists of the response time plus the time that elapses before a capacity requirement is identified. In the example on the right side of figure 5, a capacity requirement of 4 hours per SCD arises at 0 SCD. The (technical) response time is 5 SCD. With the help of DTs, the capacity requirement can be identified 2 SCD earlier. The reaction period when a DT is utilized is thus 6 SCD, and 8 SCD without DT. Since measures can be initiated earlier, capacities are available sooner. As a result, capacity control can be carried out more efficiently and logistical benefits can be gained by reducing the reaction period. Since the primary goal of backlog control is to quickly reduce backlogs, and thus schedule deviations [28], the utilization of DTs could be an effective way to achieve this.

6. Conclusion

This paper deals with the potential of DTs for production control & monitoring. Firstly, an overview of the fundamentals of production control & monitoring is given. Secondly, we illustrate different concepts of DTs. Finally, a model for the constant tracking and output is presented, potential use cases are discussed and its relevance in production control and monitoring is demonstrated in an example of application. Data generated by DTs essentially provide an information advantage, as both quality and progress data can be continuously retrieved and complement discrete data. Our findings indicate that DTs in production can contribute to organize production control and monitoring tasks more efficiently.

The implementation and the creation of DTs is a complex task due to for instance issues of heterogeneous data sources (see [33]) . Despite technical challenges, certain conditions must be imposed if such use of DTs in production control is to be effective. For instance, recording the continuous temporal sequence of a production process is only useful if the output rate is volatile and therefore planning data is inaccurate. The same applies to quality data: the acquisition of quality data in the process is all the more valuable if there are strong qualitative deviations, if rework is often necessary or if further processing is quality-dependent. A potential application area is the production of optoelectronic systems, on which adaptive models and process simulations are currently being researched. The resulting data could be linked to the PPC.

In conclusion, it is important to note that future research should further focus on how this additional information can be used to improve production control and monitoring. The application of production logistics models can facilitate the use of real-time data. However, the application of continuous data in production logistics models needs to be further explored, and the presented approach is only a first step. It is necessary to evaluate identified potentials on the basis of simulation with experimental or industrial data. Furthermore, it should be investigated how this database respectively the developed model can be used for other PPC tasks, also with regard to automation, e.g. by investigating adaptive production control.

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Biography

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