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An approach for target-oriented process analysis for the implementation of Digital Process Optimization Twins in the field of intralogistics

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Abstract

The importance of Digital Twins has increased significantly in recent years. Despite a large number of papers on Digital Twin concepts, Digital Twins are hardly implemented in manufacturing companies, especially in the area of intralogistics. Companies lack know-how, implementation concepts and methods. Thus, the potential of digital twins to improve performance in intralogistics remains largely unused, although, logistics processes have a significant impact on manufacturing performance. For lean, customer-oriented logistics, process thinking and measurement must prevail. Hence, processes should be planned, controlled, and optimized by means of Key Performance Indicators (KPI). Consequently, KPI are the pivotal point for so-called Digital Process Optimization Twins (DPOT). The focus of this paper is to develop an approach to support the planning and implementation of DPOT in the area of intralogistics. For this purpose, a process analysis method as well as an evaluation model for DPOT are presented. The approach analyzes and evaluates the processes for the implementation of DPOTs to improve the intralogistics KPI. Its advantages include the structured assessment of the processes through the DPOTs' autonomy level and the existing/ respective implementation technologies. This enables an improved process understanding with the aim to uncover weaknesses and to identify optimization potentials for DPOT.

Keywords: Digital Twin; Process optimization; Value Stream Mapping; Intralogistics; Key Performance Indicator

1. Introduction

Shorter innovation cycles and a rapidly increasing number of variants are leading to greater business complexity and to rising competitive pressure on cost and time (Günthner et al., 2013; Roeren, 2016; Langlotz et al., 2020). In order to achieve the goals, the importance of intralogistics has increased significantly. Rather than representing just a material flow technology, intralogistics is a holistic system that also includes information technology and business management aspects (Miebach and Müller, 2006). In order to remain competitive, interlinked and highly complex processes must be managed by planning and control services (Miebach and Müller, 2006). At this point, Digital Twins offer particularly great added value for planning and monitoring activities with real-time data (Pistorius, 2020). For this work, digital twins are defined as follows: A Digital Twin is a virtual, dynamic representation of a real system. It is fed with currently relevant operating data and provides information for decision support or process optimization. Capabilities of Digital Twins comprise monitoring and decision-support functions or go up to self-control systems (Klein et al., 2019). Consequently, process times can be optimized, failure rates reduced, and costs lowered in the long term. The benefits of Digital Twins are obvious. However, 78% of companies lack know-how in the realization of digital twins (Weber and Grosser, 2019). Only 12% have implemented a Digital Twin, whereby 73% offer virtual products (Riedelsheimer et al., 2020). Consequently, Digital Twins have been barely established in companies, especially in the area of intralogistics. Thus, this paper presents a novel approach for analyzing and evaluating current or future processes with regard to digital twins for process optimization. For this purpose, a methodical procedure and relevant components are described in more detail and subsequently the integration into a practice-oriented process analysis approach is presented. The core of the approach is formed by process-relevant KPIs with the aim of analyzing and evaluating the current state in order to actively derive potential for future planning.

2. Structure of the paper

This paper begins by describing the state of the Art on Digital Twins models. Afterwards, an approach for target-oriented process analysis for DPOT is presented. At the beginning, the systematic structure of DPOT in the area of intralogistics is described. Afterwards, relevant analysis components are discussed. These are KPI, Autonomy Level of DPOT and intralogistics processes. Based on this, the interaction of the components is described in the form of a methodical procedure and the practical approach for implementing the process analysis. Finally, the approach is validated on a reference model.

3. State of the Art on Digital Twins models

To date, there is no common definition of Digital Twins (Klostermeier et al., 2017; Stark and Damerau, 2019; Eigner et al., 2019; Lutz et al., 2020). However, definitions from the literature share common keywords. These include virtual representation of a real system, data exchange, real-time and predictive capabilities (Stark and Damerau, 2019).

Perception of "current" or "real-time" is defined based on individual system requirements and associated temporal limits. The goal is to complete all tasks and functions in a given environment and under all operating conditions in time (Scholz, 2005).

An overview of Digital Twin models is given in this section. Fottner, et al. developed a classification matrix for autonomous intralogistics systems (Fottner et al., 2021). The matrix consists of the dimensions task level and automation stage. Latter is divided into five sections, starting with no automation and ending with autonomy.

Stark and Damerau presented a guideline in form of an 8-dimension model which focuses primarily on Digital Product Twins (Stark and Damerau, 2019). Furthermore, a framework for classifying Digital Twins in production systems was presented by Glatt et al. (Glatt et al. 2020). Aim of the two-dimensional model of Glatt et al. is to assign and differentiate Digital Twins in production into life cycle phases. The IoT Analytics company developed a cubic model for classifying Digital Twins using hierarchical level, frequent application fields, and product life cycle phases as the three dimensions (IoT Analytics 2019).

In addition, a conceptual framework for value creation through Digital Twins was presented by Barth and Ehrat (Barth and Ehrat, 2020). A distinction is made between external and internal value generation as well as data resources. The sections are divided into cube models. Lee et al. developed a 5-stage Cyber Physical System (CPS) architecture model (Lee et al., 2015). According to this model, Digital Twins can be broken down into five stages with ascending functionality. Starting with the lowest stage, the Smart Connection, Data to Information Conversion, go up to the Cyber stage, Cognition stage and the Configuration stage.

Existing models for Digital Twins largely focus on products and production technology. A detailed model for the evaluation of processes and their KPI, has not yet been developed. Accordingly, and due to the industry challenges and advantages of Digital Twins in the area of intralogistics, this paper represents a first step towards planning of Digital Process Optimization Twins (DPOT). A DPOT is a dynamic representation of processes based on their KPI and provide information for decision support or process optimization.

4. Approach to target-oriented planning of digital process optimization twins

Figure 1 shows a Digital Process Optimization Twin in its system environment. In a high-level black box consideration, the DPOT can be compared to a controller in control engineering and the input information represents the controlled variable.

The DPOT requires process information that can be obtained from planning and control systems (PCS), expert input, or directly from the process. In the latter case, relevant data is transmitted to the DPOT. Information may already be available in the form of KPI or determined within the DPOT functionality. Process data are in parallel transmitted to the PCS by the automation pyramid. In addition, experts are able to influence PCS and DPOT, e.g., through KPI targets. Furthermore, a bidirectional exchange between PCS and DPOT takes place for the integration of more information. Consequently, depending on the use case, specific actions e.g. analyses, forecasts, self-control can be performed in DPOT. After been processed in the DPOT, KPI can be visualized, for example on a Shopfloor Board or provided for further information exchange. Likewise, processes and recommendations

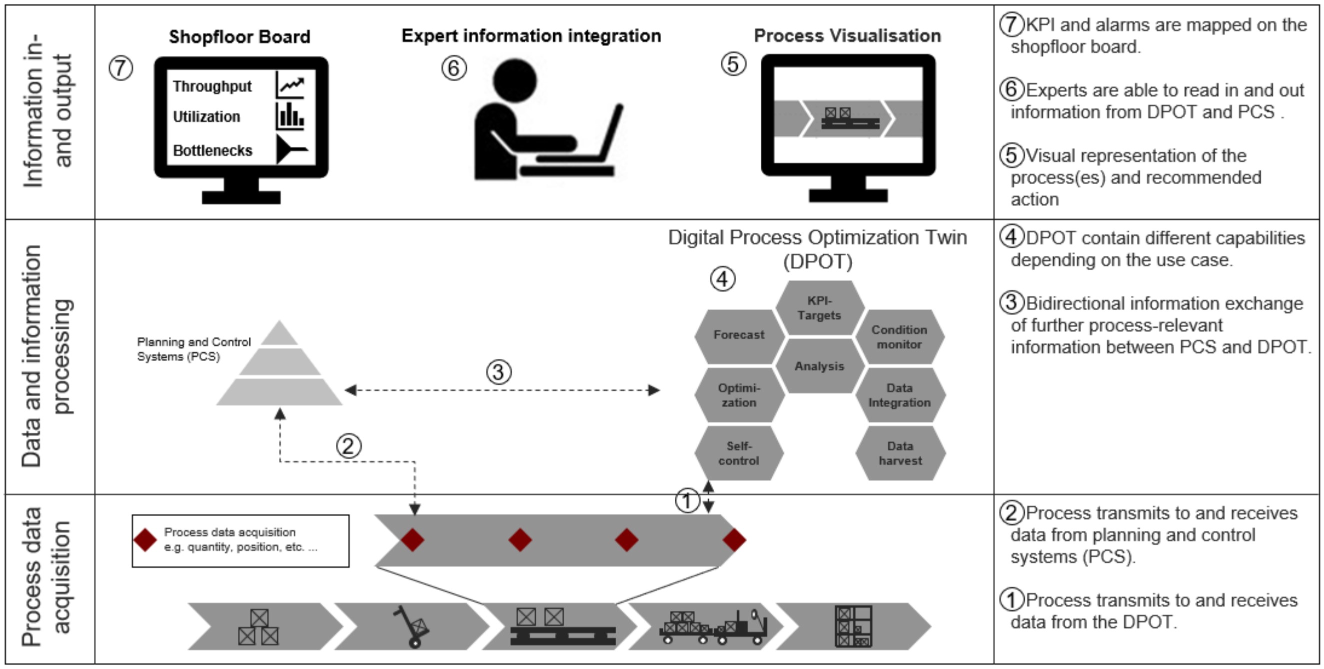

Figure 1. Digital Process Optimization Twin

for action can be visualized. The first step to support the planning of DPOT is a model to analyze the current and it's to-be level of autonomy. The model developed consists of three dimensions: KPI, autonomy level, and processes of intralogistics. Figure 2 shows the evaluation model for DPOT. The three axis are described in the following.

4.1. Key Performance Indicator

Planning, control, and optimization of processes are supported by KPI. In Figure 2, the KPI are divided into performance, quality, and cost. Performance is understood to mean the productivity of the employees as well as the systems. Quality KPIs assess the degree of targeting and errors. Costs can be recorded in both relative and absolute KPI. Often relative KPI (e.g. utilization of transport systems) are more meaningful than absolute KPI (value of stored goods). Nevertheless, the latter are important actuators for operational planning and control.

4.2. Autonomy level

The basis for partitioning the various autonomy levels for DPOT is the 5-level cyber-physical system architecture model of Lee et al.. However, this model is modified and supplemented by three additional levels. Figure 2 shows the eight autonomy levels on the Z-axis, which are described in the next paragraphs. Important to be emphasize is that the levels do not depend on each other. For example, the forecast function can be performed without analyzing historical data, or the self-control function can be performed without prior forecasting.

Collecting accurate and trust worthy data from processes (process data acquisition), is a prerequisite for a DPOT but not an autonomy level. The data can be measured directly from sensors, provided by planning and control systems such as ERP, MES and SCM, or directly integrated through experts. Considering different types of data, a seamless gateway must be ensured (Lee et al., 2015). OPC UA (GEL/65/3, 2020) and MTConnect (Jasperneite et al., 2015) are platform-independent standards for the exchange of data in the context of Industry 4.0.

Subsequently to avoid unnecessarily large amounts of data and thus a high load on the data streams the necessary data can be filtered (data harvest). An interesting aspect is the way the data is filtered respectively retrieved. Data can be transmitted to the DPOT either without filtering, or already pre-filtered e.g. in an intelligent sensor. Depending on the algorithm, this can be time or event based, among other things. Time-based filtering means that information is transmitted at defined time intervals. In contrast, event-based filtering transmits information when defined events occur. For example, if the lead time of the transportation is to be analyzed, an event-based filtering of the data, i.e. at each station, makes sense. This enables a more precise assignment of bottlenecks and potentials. Furthermore, information respectively KPI are determined. In this level, current KPI can be visualized on a dashboard without further processing steps of the DPOT. Consequently, the processes can be mapped in real time.

After data harvest has taken place, the information obtained from it must be integrated for further processing and/or storage. On the one hand, data can be stored in e.g. Enterprise Resource Planning (ERP), Warehouse Management System (WMS) or Transport

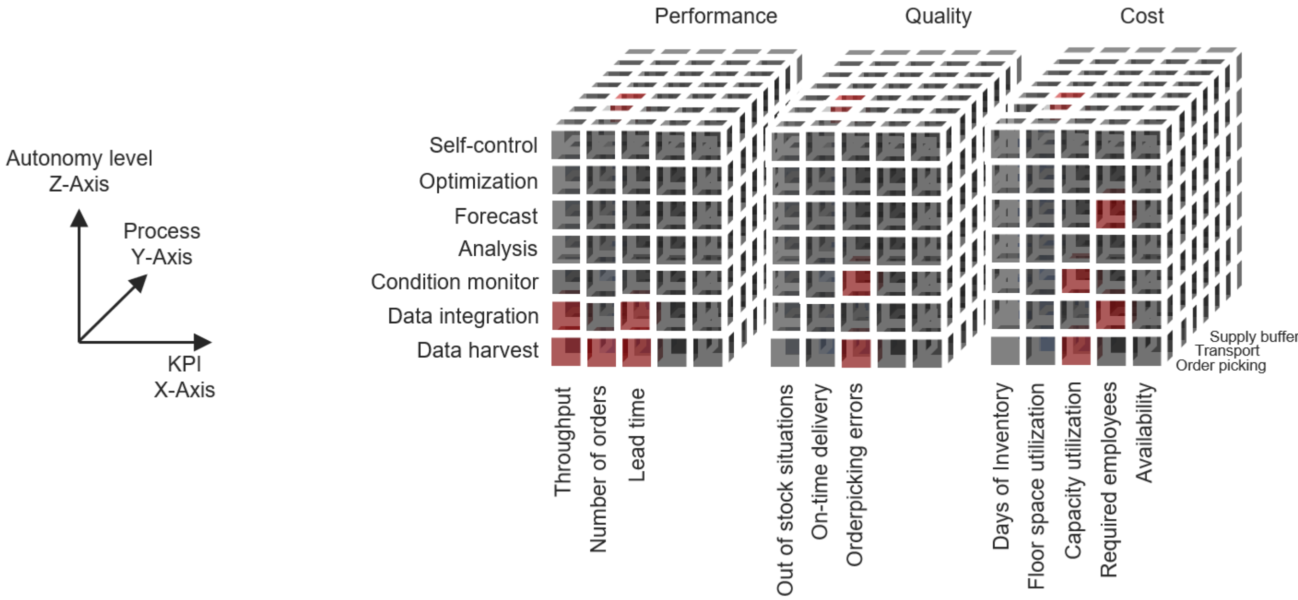

Figure 2. Model for target-oriented planning of Digital Process Optimization Twins

Control System (TCS), on the other hand, the data can also be integrated directly into the DPOT for further processing.

For the level, condition monitor, desired information is necessary in addition to the current information. Desired information can be exact values but also tolerance values. Based on this, it is possible to perform information comparisons in order to detect deviations and optimization potentials, to provide signals and thus to monitor the condition. Consequently, a condition monitoring system that compares current and target values of the actual situation represents the third level of a DPOT. For this and the following level, appropriate infographics are useful to fully convey the acquired knowledge to the users (Lee et al., 2015). For example, time deviations, system errors, etc. can be monitored and the responsible employees informed.

Another autonomy level is the, analysis' level. The goal is to generate a deeper understanding of the processes by increasing transparency. For this purpose, the analysis enables correlations and causes to be identified. For example, the on-time delivery performance in the order picking can be analyzed, as shown in Figure 2. Consequently, in case of deviations, the cause can be determined and assigned to the respective processes. The problem is, thus, solved directly by correcting the cause and hence, further delay due to it can be prevented.

The forecast' represents an additional level. DPOT enable the user to perform what-if analyses. This means that various possible scenarios can be simulated on the basis of current information in the DPOT. Consequently, the effects of the current state as well as alternative courses of action can be predicted. In addition to the forecast based on current information, already known future information can also be included in forecasts. E.g., based on the next day's order information, the required employees for order picking can be forecasted through a simulation. Furthermore, a peak load forecast in goods receipt would be possible on the basis of known delivery times of the suppliers.

In the seventh level, specific optimization functions can be performed. Different scenarios can be compared and evaluated. For this, alternative scenarios and factors for the scenario evaluation must be determined. As a result, the system provides the user with the best solution, but the decision is still up to the user. For example, if there is a short-term employee scarcity (due to illness), different scenarios can be simulated to determine the best employee - position/asset allocation. To avoid bottlenecks and waiting times as well as to ensure on-time delivery and lead times, the correct order sequence is important. To achieve this, a simulation and evaluation based on current information is useful. The Aim is to determine the best sequence for the current specific situation.

The self-control level, shown in Figure 2, represents the highest level of autonomy. Decisions can not only be made by means of suitable algorithms and KPIs, as in the previous level, but can subsequently be fed back into the process in an automated manner. Human intervention is no longer necessary for this, but still possible. The sequence simulation from the seventh level can be used as an example, with the difference that in the self-control level the optimal sequence is automatically entered into the processes. The result can be, among other things, retrieval and transport commands as well as order reprioritizations.

4.3. Intralogistics Processes

Intralogistics Processes are the third model axis (Y-

Axis). The user can decide which processes are to be compared with each other. This can be a high-level view or comparison, for example the whole material flow process or also a more detailed view, e.g. of the individual transport processes. The model can, thus, be applied to different hierarchy level.

4.4. Analysis method for Digital Process Optimization Twins

In this section the "Analysis method for DPOT" is introduced and the structure is explained. The method aims to determine the current state of the processes using the autonomy levels of the DPOT and to indicate the technologies used (Figure 3), based on Value Stream Mapping 4.0 (Meudt et al., 2016) and logistics-oriented Value Stream Mapping (Knössl, 2013).

A process optimization is usually initiated with a solid as-is-analysis phase to identify processes, data, KPI, and weaknesses. Value stream mapping (VSM) has been established itself as a suitable method for the analysis phase for manufacturing companies. The origin of value stream mapping can be found in the method developed by Rother and Shook (Rother et al.;2011). The aim is to identify waste in the value stream by means of analyzing relevant material and information flows. Additionally, important data and KPI are collected. Next, vulnerabilities and waste in the processes can be identified and subsequently improved using the principles of lean production and logistics in value stream design.

Due to increasing process digitalization during the Industry 4.0 trend and the resulting increased focus on the flow of information, the value stream analysis of Meudt et al. (Meudt et al., 2016) was further developed into Value Stream Analysis 4.0. The main modification is the investigation of information logistic waste through a swimlane diagram. The diagram documents the media for the data and KPI of the individual process steps. This leads to better visualization and transparency of the information flow as well as opportunities for improvement in the digitization of processes (Bäuml et al., 2019).

Another development of VSM is the logistics-oriented value stream mapping by Knössl (Knössl, 2013). The focus is on the mapping, visualization, and analysis of logistics processes. Logistics processes have a significant impact on the performance of production processes. At the same time, in the usual view of lean management, they are non-value-added activities. Nevertheless, logistical activities are necessary to make the product available to the customer. This "service value" must be generated with as minimal effort as possible (Knössl, 2013). Standardized symbols and process modules have been developed for this purpose. Both include the logistical function of a process and the process attributes (Klenk et al, 2013).

Based on these three methods, an analysis method for the determination of the autonomy level for planning, control, and optimization of logistic processes in intralogistics is presented. The goal is to create a data basis for the evaluation model. As a result, a novel analysis method, which is based on an established procedure, is used to provide usability for companies.

4.5. Analysis approach for planning of Digital Process Optimization Twins

In the following the steps for the method are described (see also Figure 3, which is based on the model of Figure 2).

First step of the analysis is the documentation of the relevant intralogistics processes of the given company, e.g. picking, transportation and buffering. In a second step, typical data such as shift models, duration, etc. are captured in the process boxes and supplemented with necessary process KPI. Below the process boxes a swimlane diagram is shown with the levels "Process data acquisition", "Data harvest", "Data integration", "Condition monitor", "Analysis", "Forecast", "Optimization", "Self-control". In the third step, the existing technologies are added to the respective autonomy levels, for example, scanning and RFID for process data acquisition or shopfloor management for condition monitoring.

In the fourth step, KPI (like lead time, capacity utilization, or error rate) are connected to their autonomy levels respectively the associated technologies by means of a point symbol. After the four steps the "Analysis method for DPOT" is completed and an overview of the current processes, KPI, and their autonomy levels for planning DPOT is given. Based on this, weaknesses and optimization potentials be identified as well as goals derived. For this purpose, processes can be compared with each other on the basis of the existing KPIs and autonomy levels. Consequently, it is possible to identify which KPI are present or missing in the processes, at which autonomy level they are mapped, and which technologies used for it. In concrete terms, this means that optimization potentials can already be uncovered. For example, if the order picking errors are high, it makes sense introduce a more sophisticated DPOT in order to reduce them. In order to implement the goals with as little effort as possible, the first step can be to concentrate on the transfer of already established technologies from other processes. Furthermore, the method enables the targeted filtering of processes, KPIs and autonomy levels. Thus, it is possible to focus purely on the optimization of a KPI, for example the lead time. In addition to the transfer possibilities, wastes are also uncovered and examined to determine whether optimization potentials exist. In particular, data is often collected but not processed further. In this case, it is necessary to check whether further processing is helpful. Thus, the whole approach offers added value for the planning of DPOT in order to cope with the increasing challenges in intralogistics described at the beginning.

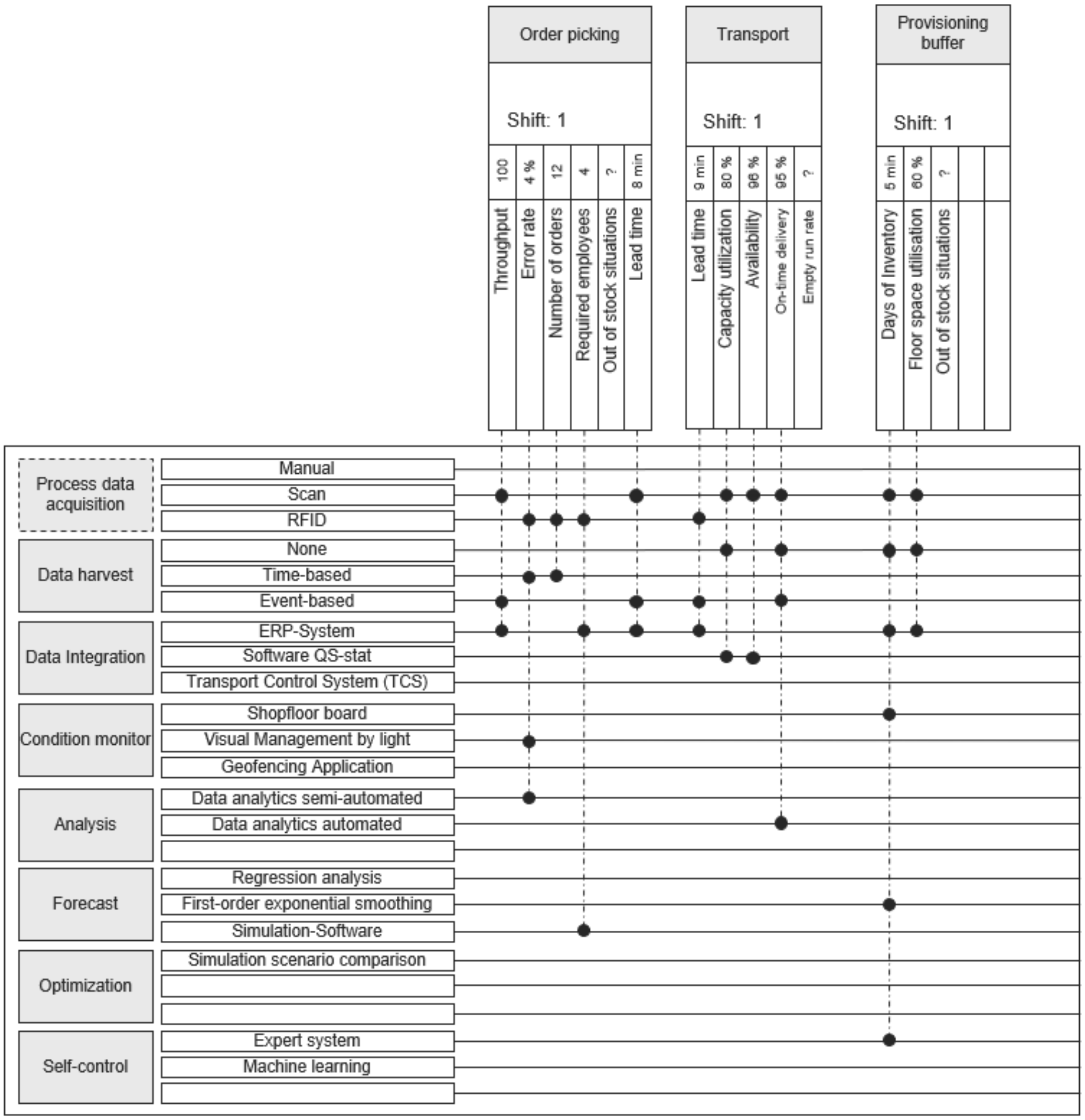

Figure 3. Analysis method for planning of Digital Process Optimization Twins

5. Validation

The approach for target-oriented process analysis for the implementation of DPOT was applied to a reference supply process. For this purpose, the material and information flow of the learning and model factory of the Technology Center for Production and Logistics Systems (TZ PULS) of the Landshut University of Applied Sciences was investigated. The learning and model factory is representing the production and logistics of a small to medium-sized manufacturing company. The production and assembly of load handling devices in six different variants has been realized therefore. Recording of the material and information flow was achieved by using the "Analysis method for DPOT" outlined in Section 3.4. Figure 3 shows an extract of the process steps identified and considered in this paper (order picking, transportation and buffering). These processes are used as examples to explain the approach for planning DPOT. In the first step – picking – the required orders are picked manually. To monitor this process, the lead time per order, the error rate in percent per shift and the number of orders per working day are currently determined. As shown in Figure 3, the lead time per order is recorded by a scan at the beginning and end of each order. Subsequently, the data are transferred to the ERP system. A similar process is used for the error rate. Furthermore, the KPI is additionally supported by a pick-by-light system. A semi-automatic problem analysis is also performed. The errors and problems are evaluated with the help of data analytics methods. Once picking is complete, the goods are transferred to the next process. In this step, a tugger train drives from the source (=picking) to the sink (=supply buffer). Within this process, the lead time per order and the capacity utilization during loading and unloading are recorded by means of an RFID system. The availability of the means of transport is recorded in the QS-stat. software. As a fourth KPI, the on-time delivery can be measured. This is determined by means of the time stamp during unloading. It is displayed on the shopfloor board.

At the supply buffer, which is based on an electronic kanban control, the following KPI are used for process monitoring. The Days of inventory can be predicted for future orders. The information required for this can be obtained from already known demands from the ERP system or by means of forecasts. Based on this, in the same way replenishment orders can be created in defined time periods. Electronic kanban control is used to automatically control the material flow. An order is transmitted electronically to the upstream process by entering a stock retrieved into the computer (= terminal) near the supply buffer. In addition, when the tugger train is unloaded, the floor space utilization is systematically recorded by barcode scanning with the essential information of container type and number. This information is compared with the space information in the ERP system. After the goods have been delivered to the supply buffer location, further process steps are carried out. Furthermore, deviations can also be traced back to the process responsible.

Processes can be compared with each other by means of this method. By comparing the processes and thus increasing transparency, the differences in the autonomy levels can be revealed. The goal is to eliminate the weaknesses in the processes through target-oriented DPOT and to uncover potentials. A first optimization would be that the lead time of the picking process as well as the transport availability are visualized on a shopfloor board and a warning should be issued if tolerances are exceeded. Moreover, the question arises why the availability of the means of transport is recorded in the QS-stat. software but not analyzed further. The lead time is recorded in both the picking and the transport process. However, this raises the question why different technologies (scan & RFID) are used. The analysis also shows that the KPI, days of inventory, is only determined in the supply buffer. However, this KPI is just as important for the order picking process. Since the processes are quite similar, transferring the technologies to the order picking process should not require much effort. In the current transport process, it is noticeable that the empty run rate is not evaluated. Since the loading and unloading processes are already tracked using RFID systems, the empty run rate could easily be derived from this information. In addition, as utilization is already recorded in the QS-stat. software, it would be sensible to further monitor and analyze this information to increase efficiency. Beside this, the utilization of the resources in the other processes is equally important. The goal should be to be able to forecast the resource utilization on a shift-by-shift basis. Furthermore, the numbers of out of stock situations in the supply buffer is not recorded. At best, the DPOT could predict peak loads and prevent supply bottlenecks through optimization functions.

6. Conclusion and future work

This paper presents an approach for the analysis of existing or future processes with regard to the application possibilities of Digital Process Optimization Twins in intralogistics. The analysis method enables a KPI-oriented identification of the current status, and consequently weaknesses within the operation processes and DPOT applications. The approach provides the ground for further development and implementation of optimization concepts and future digitalization strategies. It is also the basis for a cross-departmental and cross-hierarchical understanding of DPOT implementation and technological requirements. The next step is to investigate level-specific functions and define necessary components of the DPOT. The approach has already been validated in the learning and model factory of the Technology Center for Production and Logistics Systems (TZ PULS) at Landshut University of Applied Sciences. However, a final validation in a real manufacturing company has yet to take place. Furthermore, it is important to derive implementation concepts that can be adopted in intralogistics practice.

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