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Development of a decision support app for short term production control to improve the adherence to delivery dates

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Abstract

In manufacturing, adherence to delivery dates is one of the main logistic goals. The production control department has to cope with short-term deviations from the planned route sheets. Because of unforeseen disruptions, e.g. machine breakdowns or shortage of material or personnel, in some situations, the promised delivery date to the customer is at stake. In practice, a fast and reasonable decision on how to deal with the delayed order is required. This decision process is often based on a qualitative analysis relying on the planner's subjective assessment of a complex situation. To improve the quality of possible countermeasures this paper presents an application, which supports the decision process through a quantified analysis using real-time data from business application systems in combination with a simulation of the value stream. The developed app is part of the decision process and estimates the effect of selected countermeasures to accelerate a delayed order. Performance indicators illustrate the effect of the countermeasures on the specific order as well as the whole system. This approach empowers the planner to assess unforeseen situations and aims to improve the quality of the decision-making process. This paper describes the architecture of the application, its simulation ecosystem, the relevant data and the decision process to select the most effective countermeasures.

Keywords

Production Control; Decision Support; Discrete Event Simulation; Adherence To Delivery Dates; Disturbance Management

1. Introduction

The order fulfilment process in manufacturing companies is developing a higher complexity due to the increasing number of product variants and rising demand for individualized products [1]. In addition to this internal complexity, the market side demand fluctuations are of high and growing relevance for companies pushing them to increase the flexibility of their production system [2]. To cope with internal and external complexity, companies have to establish efficient and effective production control systems. These systems are characterized through a fast and robust adaption process in the context of unexpected disturbances. Therefore, production controllers face the challenge to deliver high-quality decisions in a complex environment to maintain an optimum between logistic performance and logistic costs. The main logistic target of manufacturing companies is adherence to delivery dates [3] and its importance is increasing within the supply chain [2]. It is expected that knowledge-based systems such as decision support systems can play a vital role to support the decision process in production planning and control [4]. In this paper the decision support system, which is developed within the research project "EkuPro – Decision support for short-term production control”, is described. The focused research question of this paper is as followed: How must a decision support system be designed to support production control in improving adherence to delivery dates?

2. Motivation

Successful companies strive towards low inventories and high adherence to delivery dates. Such companies are leaders in punctually delivering to their customers by which they gain trust and avoid high costs and penalties from delayed orders [5]. To realize their logistic performance they have implemented high performing production control systems achieving a closed-loop production control [6]. Production control monitors the execution of the planned production program and therefore constantly compares the planned and actual output of the production system and engages if deviations from the plan occur. The tasks of production control include the releasing and sequencing of orders as well as the capacity control of the resources [5]. Unforeseen incidents, such as machine breakdowns, shortage of material or personnel challenge companies to meet promised delivery dates. In this situation, the production planner has to deliver a fast and profound analysis of the situation in order to decide how to proceed with the affected orders. If an order falls late due to the disturbance with respect to its production schedule, various actions to accelerate exist. The range of actions varies from shortly increasing production capacity (additional shifts) through prioritizing the delayed order to shifting the release of competing orders to a later timeframe.

Operational application systems such as ERP (Enterprise Resource Planning), MES (Manufacturing Execution System) or APS (Advanced Planning and Scheduling) support in the production planning [7] but don’t assist in the selection process of the right countermeasure. Their functionality supports the optimal scheduling of all manufacturing orders under the restriction of the available resources and the promised delivery dates. Due to this focus, these IT-systems do not support daily operational decisions. These choices concern for example how to handle a single delayed manufacturing order or the question, which measures are necessary to accelerate that delayed order to meet a promised delivery date. Therefore, production planners rely on their subjective assessment of the situation, which results in an unstable decision quality as well as a low adherence to delivery dates. Today’s application systems lack to support with a quantified analysis as well as a prognosis of the effects of possible countermeasures.

In the proposed methodology, an application is developed which focuses on the decision support for the acceleration of one specific delayed order. The developed decision support application considers monetary and logistic effects of possible countermeasures. The impact of the measures is estimated via a discrete event simulation of the considered production system and delivers a quantified basis within the decision process.

3. State of the art

The state of the art shows the research focusing on system support for production planning and control, simulation and decision support systems for production control in the context of adherence to delivery dates.

3.1 System support for production planning and control

In practice, companies rely on ERP, MES or even APS systems to support their tasks in production planning and control. Born out of MRP (material requirements planning) systems, which handled the material planning of a company, ERP systems are nowadays the information backbone for most companies across all industries [8]. They support the complete order fulfilment process from a customer order over the product manufacturing to the delivery and the invoicing of the order. ME systems gather information from the shop-floor level on personnel, work orders and capacity of resources and link them to the planning process in the ERP systems [9]. Therefore ERP and ME systems operate in different timeframes whereas ME systems have a shorter timespan since they mainly focus only on production-related processes. APS systems are a functional extension for ME and ERP systems. They provide more powerful methods based on mathematical optimization for order sequencing, scheduling and resource allocation in comparison to the basic concept of material requirements planning (MRP). In the context of decision processes within production, ERP and ME systems provide information on the order status, the availability of resources and material as well as aggregated key performance indicators such as OEE or adherence to delivery dates. Therefore, the information basis for the decision support application, which is described in this paper, also relies on data from the ERP or ME system.

3.2 Simulation in production and logistics

Discrete event simulation (DES) is a method for analysing dynamical independencies in production and logistics with the goal to improve the design, control and operation of the material flow, the resources and the information flow [10,11]. Latest research has been conducted within the fields of simulation integration in enterprise applications, automatic model generation and collaborative modelling and simulation [11]. In automatic model, generation approaches a simulation model is not created manually but is generated from external data sources [12]. Automated model generation reduces the effort to build up models and helps to standardize simulation models using three ways. Parametric approaches use predefined building blocks stored in a simulation library, which are then combined and parameterized for the modelling of a specific system. Structural approaches use a structural description e.g. a factory layout and hybrid approaches combine both methods. Most of today's approaches are hybrid since they are using both parametric and structural data [13]. In the development of a simulation for a production system, the distinction is made between planning related and operations related simulation. In contrast to simulation in the production planning phase, operation related simulation supports the analysis of the actual behaviour of the production system under various aspects [14]. The operation related approach, discrete simulation helps to quantify the production system behaviour in a certain state through simulation scenarios. By modelling different strategies for production control tasks, e.g. adapting the order release policy or resource capacities in the simulation, the production control department is able to use simulation scenarios as decision support for the evaluation of their control options.

3.3 Decision support systems

"A decision support system (DSS) is a computer-based system that supports the choice by assisting the decision-maker in the organization of information and modelling of outcomes" [15]. Every decision a human makes is the attempt to change an unsatisfactory situation into a future satisfactory situation [16]. The decision process starts with an estimation of the current situation following the anticipation about the effect of certain or multiple actions, which create the desired future situation. Therefore, every decision process inherits a guess about the future. In the process of decision making several alternatives have to be studied and evaluated in terms of their implications on the system and thus their purpose in reaching the desired goal [17]. In a complex environment, the number of alternatives might be too large for a quick decision or the interdependencies of the regarded system are too multi-layered for a human to comprehend. In this case, a decision support system helps to better understand the interdependencies of the system [18] and supports in filtering for relevant data in the assessment of the situation. The focus on relevant parameters of the system helps the decision-maker to build up actionable knowledge [19]. This leads to a reduced effort within the decision process and a reduced count of suboptimal decisions. Therefore, decision support systems improve the process of decision making as well as the quality of the decision [20].

A decision support system consists of three main components (see Figure 1). The data component contains the necessary functions to gather and transform data to draw conclusions from it. The model component simplifies the considered system for understanding its behaviour. The modelling process summarizes and accumulates the data in order to compare different alternatives and their effect on the system. Different types of models from mathematical, optimization or financial models are possible within a decision support system [21]. Finally, the user interface receives data input and presents analytics, which is carried out by the DSS.

4. The concept and design of the decision support system

4.1 Countermeasures to accelerate a delayed order and their cause-effects

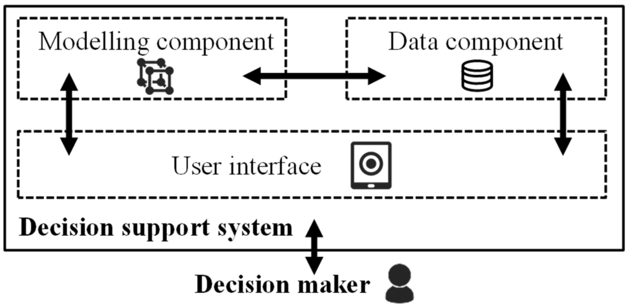
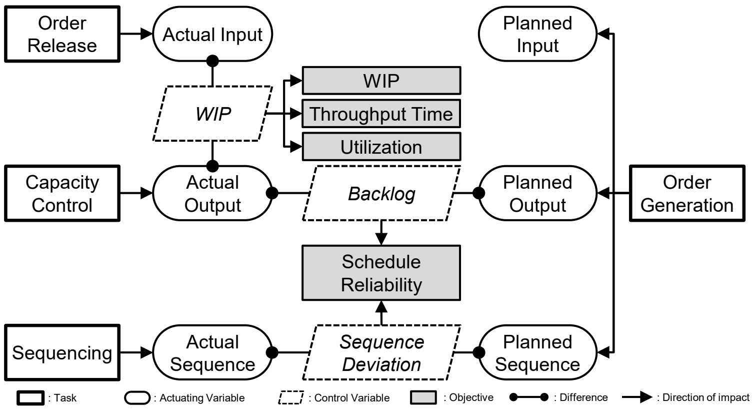


Figure 1: Components of a decision support system based on [15]

The development of the proposed decision support application aims to support the comparison of different countermeasures for a delayed manufacturing order. The main goal is to empower a production planner in the decision making on how to deal with a delayed order and to assess if it is possible to catch up and deliver in time. In the research project, six practical and applicable countermeasures were developed with industry employees to form a manageable set of alternatives. This straightforward approach helps the planner to quickly model different scenarios, which are then simulated. The six possible countermeasures are a "batch split", "delaying a production order", "changing order priorities", "substituting resources", "changing resource capacities" and "subcontracting" (see Table 1). In the following, the different countermeasures are explained by their chain of action in relation to the manufacturing control model [5]. Each countermeasure develops its effect by influencing the actuating variables of the control model.

Through a batch split the batch parts are processed in parallel, thus the first part is started earlier at the succeeding work system. Therefore, the actual load is decreased in that timeframe which results in earlier completion of the production order. Delaying a competing order in favour of the delayed one frees up resources (reduction in *actual or planned input*) and accelerating the remaining orders through an earlier start. A change in the priority of the delayed order lifts its status to a rush order. Therefore, it is preferentially processed at the workstations (change in *planned or actual sequence*), which reduces the waiting times, and thus the throughput time of the order. Through the substitution of a resource, e.g. the worker or the machine the process times or the planned start of a manufacturing order can be adjusted resulting in earlier or faster production. The same logic applies to the increase in resource capacities. By adjusting personnel or machine shift plans the actual output of the production system is increased, which accelerates the delayed as well as the rest of the production orders. Subcontracting production orders decreases the load (reduction in *planned or actual input*) on the production system by freeing up capacity for the delayed order.

Table 1: Cause-effect relationships of countermeasures and actuating variables based on [5]

Countermeasure	Actuating variable	Manufacturing control model
Batch split	Actual input	
Delaying a production order	Actual or planned input	
Changing order priorities	Planned or actual sequence	
Substituting resource	Actual output or sequence	
Changing resource capacities	Actual output	
Subcontracting	Actual or planned input	

4.2 The architecture of the decision support app

The decision support systems consist of two main components. The first one is the web application, which presents an interface to the user, and the second one is the simulation model, that runs in the background (see Figure 2). The user interface is designed as a web application to offer access from a variety of devices. It is used to model different decision scenarios and to analyse the simulation results. A scenario forms a set of multiple countermeasures, which are possible to accelerate the delayed order. The simulation is realised in “Tecnomatix Plant Simulation” which is a commercial DES tool developed by Siemens PLM Software. The simulation model is based on the toolbox and platform WOPS (“Wertstromorientierte Produktionssteuerung”), which is a verified toolset to simulate production systems developed at the Laboratory for Machine Tools and Production Engineering (WZL) [22]. For the decision support app which is realized in “EkuPro” WOPS was extended to correctly model the six relevant countermeasures.

In order for the tool to be used in a real production control environment, some requirements in the design have to be considered. The user is guided through the decision process, which is structured in three sections (Figure 2). Most importantly, the DSS has to produce realistic estimations about the production system for selected alternatives in order to be credible and helpful. Therefore, the simulation relies on live data from the business application systems (ERP) to have a realistic starting point (data component). The data which is used from the application systems is described in Table 2.

Table 2: Relevant input data from application systems to parametrize the simulation

Input data	Source	Changeable control properties in a decision situation	
Master production schedule			
└ Scheduled production orders	ERP	yes	*resource order allocation, planned start time, order priority*
└ Partially confirmed production orders	ERP		
└ Production order properties	ERP	yes	*resource order allocation, order priority*
Resource availability			
└ Worker shift plan	ERP	yes	*worker attendance timeframe, worker qualification, workforce quantities*
└ Machine shift plan	ERP	yes	*machine availability time frames*
Product master data			
└ Route sheet	ERP	no	
└ Bill of material	ERP	no	

The live data is gathered via an export from the ERP system and then uploaded from the user in the first phase of the decision process. The data is used to parametrize the simulation model in order to reflect the current state of the production system.

5. Decision process with app support

The decision process starts with a relevant disruption (Step 1 in Figure 2) from the production schedule for a certain production order. This disruption can be the sum of previous delayed process steps or can occur instantly if a necessary resource becomes unavailable. In this situation, clearance is required on how to proceed with the delayed order. First, an assessment is carried out if the order is going to be finished on time considering the current production schedule and utilization of the production system. Therefore, the current state of the production system is modelled. It is based on a snapshot of the production system using data from the ERP or ME system, which is imported via the user interface (Step 2). The user enhances the dataset with the latest state of information about resource availability and chooses a simulation timeframe. By finishing this step, the decision support system incorporates all the necessary information to simulate the status quo. Within the tool, we refer to this scenario as a base scenario, which does not incorporate accelerating measures.

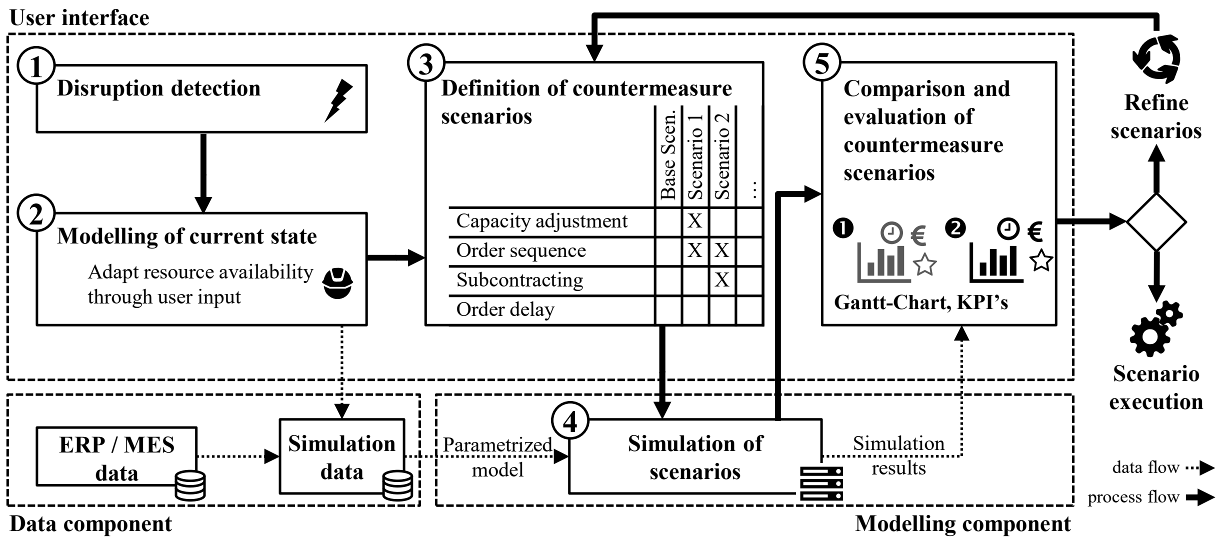


Figure 2: Steps of the decision process within "EkuPro"

The planner can simulate the base scenario on its own or he can directly add scenarios to the simulation run if countermeasures seem to be necessary by all means (Step 3). The additional scenarios are modelled within the web application. While activating certain countermeasures, the planner has to check their general feasibility in the context of working time acts, agreements with the working council or availability of extra needed staff. After modelling the scenarios, the simulation is triggered and the results are presented in the user interface (Step 5). In this step, the planner evaluates which scenario is the best choice to accelerate the delayed order on the basis of time related as well as monetary key performance indicators. The simulation gives an estimation of a realistic internal completion date for each possible scenario. With this information, it becomes transparent if the promised delivery date is at stake or if a certain countermeasure scenario can accelerate the order. The evaluation uses dashboards and lists to compare the scenarios. The dashboards visualize the order network via Gantt chart, a histogram for the adherence to delivery dates, key performance indicators (WIP, throughput time, utilization, operational costs) as well as a diagram to identify capacity bottlenecks (Figure 3). Relying on this set of transparent information the planner either refines the decision scenarios and starts a new simulation run or decides to execute the set of countermeasures. This marks the end of the decision support process.

Histogram for adherence to delivery dates in daily time buckets

Key performance indicators for scenario comparison

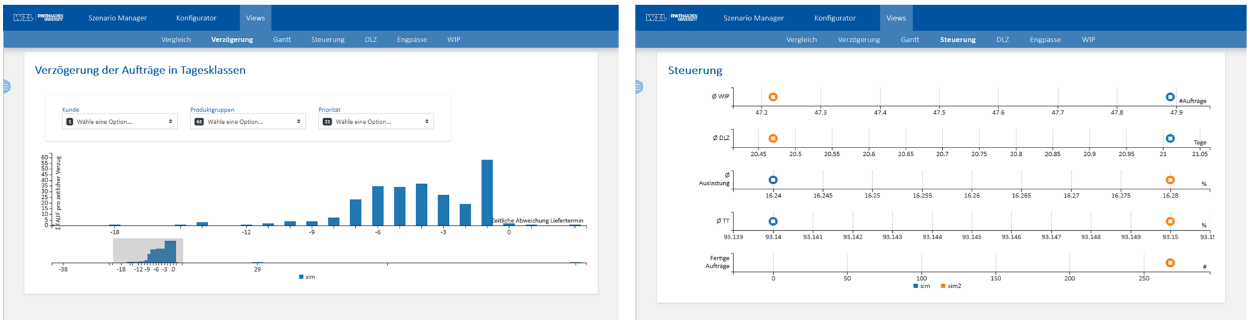


Figure 3: Example analytics dashboards of the DSS

5.1 Expected improvements using the DSS

By estimating the effects of alternative countermeasures or their combination, the decision support app aims to improve the decision process through an increase in decision quality as well as analysis and decision latency (see Figure 4). By standardizing the analysis step through a standard procedure, which uses a simulation delivering an estimation of the production system behaviour, we aim to reduce the time span of this phase. The user-focused visualization of the simulation results delivers a reduction potential for the decision latency. In comparison to the decision without the support system, the decision-maker does not have to carry out manual analytic steps or search for information in the ERP or ME system. He is guided through the evaluation through familiar dashboards, which also help to decrease the time span of the decision latency. A major improvement is expected within the decision quality, in this case, the probability that a certain set of countermeasures accelerates the delayed order. By estimating the system's behaviour, countermeasure alternatives, which have an insufficient effect on the internal delivery date, are ruled out within the decision process.

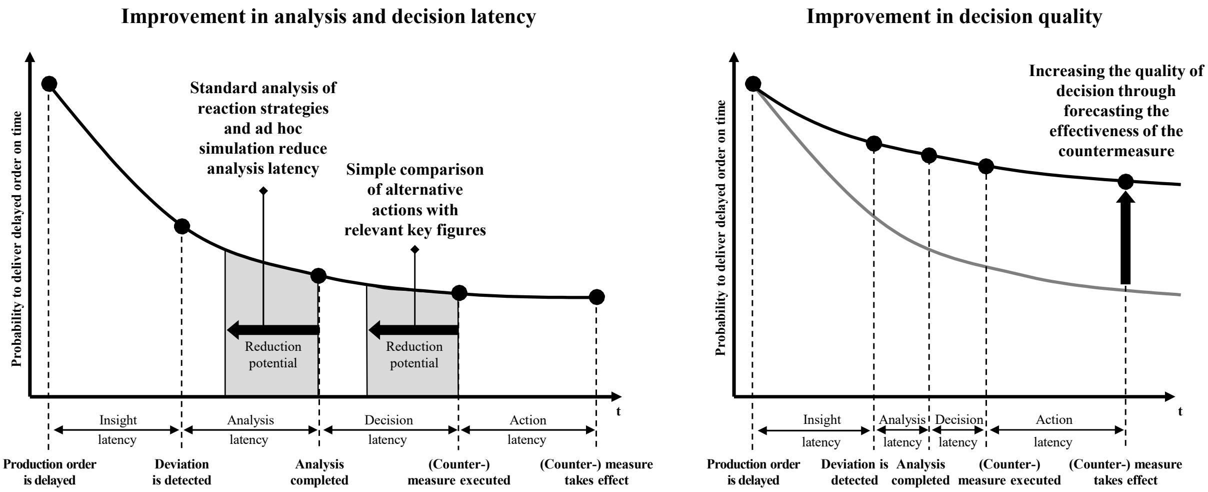


Figure 4: Improvements in the decision process based on [23]

6. Summary and outlook

The proposed decision support system is currently finalized. After that the real life evaluation is going to be started within medium sized companies. In the evaluation phase, the app is going to be used to support the production control of a manufacturer for clamping technology. Out of this phase, we are going to gather feedback through a structured questionnaire on the usability as well as the usefulness in various decision situations.

In summary, we introduced a decision support system, which empowers production planners to choose the most effective set of countermeasures in order to accelerate a delayed order. The proposed decision support system is based on discrete event simulation to estimate the behaviour of the production system by applying different countermeasure scenarios. The described DSS is developed within the research project "EkuPro – Decision support for short-term production control". The next step within the research project is the validation of the tool in the operative daily routine by the industry project partners. Based on the research results from the practical evaluation an assessment is possible to what extent a decision support system which uses discrete event simulation can help within production control to improve internal adherence to delivery dates.

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Biography

Felix Steinlein (*1989) works as a project manager and scientific assistant at the Institute for Industrial Management (FIR) at the RWTH Aachen since 2017. Before that, he gained experience in operations at Bosch and developed a strong background in lean management. His research focus lies within production planning and control, process analytics as well as enhancing operations with digitization.

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Prof. Dr.-Ing. Volker Stich (*1954) has been head of the Institute for Industrial Management (FIR) at the RWTH Aachen University since 1997. Prof. Dr.-Ing. Volker Stich worked for 10 years for the St. Gobain-Automotive Group and lead the management of European plant logistics. His research focuses on operations management, logistics and business applications systems.