CPSL
CONFERENCE ON PRODUCTION SYSTEMS AND LOGISTICS
CPSL 2020

1st Conference on Production Systems and Logistics

A Framework for Online Detection and Reaction to Disturbances on the Shop Floor Using Process Mining and Machine Learning

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Abstract

The shop floor is a dynamic environment, where deviations to the production plan frequently occur. While there are many tools to support production planning, production control is left unsupported in handling disruptions. The production controller evaluates the deviations and selects the most suitable countermeasures based on his experience. The transparency should be increased in order to improve the decision quality of the production controller by providing meaningful information during his decision process. In this paper, we propose a framework in which an interactive production control system supports the controller in the identification of and reaction to disturbances on the shop floor. At the same time, the system is being improved and updated by the domain knowledge of the controller. The reference architecture consists of three main parts. The first part is the process mining platform, the second part is the machine learning subsystem that consists of a part for the classification of the disturbances and one part for recommending countermeasures to identified disturbances. The third part is the interactive user interface. Integrating the user's feedback will enable an adaptation to the constantly changing constraints of production control. As an outlook for a technical realization, the design of the user interface and the way of interaction is presented. For the evaluation of our framework, we will use simulated event data of a sample production line. The implementation and test should result in higher production performance by reducing the downtime of the production and increase in its productivity.

Keywords

Disturbance Management; Deviation Detection; Production Control; Process Mining; Machine-Learning; Internet of Production; Decision Support

1. Introduction

The high number of customer demands for individualized products with short delivery times leads to increased perceived complexity for companies. Not only the requirements of end-users but also those within a supply chain are rising and increasing the requirements for companies' order processing [1]. In order to meet these requirements, companies must design efficient production systems that are optimally aligned with the conflicting goals of logistics. An efficient configuration of the production system also includes robust handling of internally and externally induced disturbances. Currently, the task of disturbance management is the responsibility of the production controller. The production controller faces the challenge of making high-quality decisions for selecting a suitable countermeasure as quickly as possible. The different goals of the production and those of the customers must be weighed against each other, which is very difficult due to

DOI: https://doi.org/10.15488/9681 publish-Ing.

the complex interdependencies on the shop floor. Often the production controller is insufficiently supported by IT systems and therefore relies on experience. In the area of production planning and control, it is expected that decision support systems will improve your decision-making processes and reduce the probability of making the wrong decisions [2]. Classical methods of production control are not able to cope adequately with current developments and ongoing changes, therefore the aim of this research is to develop a decision support system to improve decision quality [3]. To address these issues, the paper presents a framework for online detection and reaction to the disturbances on the shop floor using process mining and machine learning.

2. State of the Art

This section explains the terminology used in production control and deviation management in order to place the work in this context. It continues with a short definition of decision support systems and focuses on the current state of research in the area of detection and response to deviations. For this purpose, the approaches are structured in various groups, which differentiate by the used approaches for supporting the production control in handling the deviations.

2.1 Terminology

Production Planning and Control

Production planning and control (PPC) aims to deliver the customers' products in the right quantity and quality on time with minimal inventory and high utilization of the company's resources. To meet the requirements of an economic production line, production planning plans the necessary operations for the production of the product [4]. The material, resource and employee capacities are taken into account in the planning process. A distinction is made here between rough and detailed production planning. After the rough planning and the termination of the production orders, production control starts with the detailed planning of the operations. Production control also has the tasks of order and resource control. Within these latter tasks, the production controller tries to ensure adherence to the production plan [5].

Disturbance Management

The production is a dynamic environment with disturbances and deviations that must be dealt with as part of production control. For this reason, the task of deviation management plays a decisive role in production control [6]. To understand disturbance management, first, we define the deviation and disturbances in the next paragraph. Thereafter, disturbance management is defined as a part of production management.

Disturbances are regarded as unplanned and unpredictable deviations from a planned state, which have a direct influence on the process chain. Without intervention, a malfunction is accompanied by a reduction in the performance of the production system [6]. Deviations, on the other hand, are identified by comparing planned and actual values. Deviations differ from disturbances in a way that a deviation does not necessarily have negative consequences for a production system. Only when a certain tolerance corridor is violated, it will be referred to as a disturbance. Regular violations of the tolerance corridor are referred to as systematic disturbances. Irregular deviations occur in the case of accidental disturbances. Since disturbances are defined as differences with a negative impact on the plan, it is the task of the production controller - following the definition of production planning and control - to realize plan compliance. Therefore, disturbance management is to be regarded as part of production control [7].

2.2 Decision Support Systems

Decision support systems (DSS) are IT-based systems, which enable the users to access data across the company to analyze it and evaluate different alternatives [8]. The goal of DSS is to improve the quality as well as the responsiveness within the decision-making process of the user. Due to the tasks of a decision support system, Sauter [9] structures DSS into a data component, a model component, and a user interface. To achieve the goal of a DSS, the data component compiles data from various sources in the company and puts it into logical relation. The data is then processed in the model component to create statements about possible future alternatives. The models are tailored to certain questions and can range from simple to complex mathematical models. The evaluation of the models is done via a user interface, which enables easy operation of the DSS. In this way, the user can not only see the results of the model but also make adjustments to a model. The adaptation of the model as well as the possibility of independent data analysis distinguishes DSS from other decision-support options, e.g. a neural network, which is only adapted to one specific decision situation [9]. For designing a DSS, four criteria are relevant: "robustness, ease of control, simplicity, and completeness of relevant data" [8].

2.3 State of the Research

This section focuses on the state of the current research in the fields of disturbance management and compares different approaches to support the production controller in automatic disturbance handling. Various approaches exist to support knowledge-based tasks and decision support in the company. The approaches in production control and disturbance management can be divided into the approaches of methodical support, simulation-based support, and machine learning-based support.

Meissner [7] develops adaptive deviation management which enables the production controller to classify deviations. The classification helps in differentiating the level of criticality and the kind of countermeasure, which is required to handle this deviation situation. Meissner develops a reaction-strategy-matrix for integration in production control, however, automatic support for the production controller is not developed.

Galaske and Anderl [10] present a simulation aided decision support tool for the disruption management of Cyber-Physical Production Systems. Interdependencies between the different disruptions events are analyzed, resulting in a consistency matrix. Based on the consistency matrix, the different events are clustered, allowing to create disruption scenarios for the different categories of events. For every disruption scenario, several actions are defined. A simulation tool is used to evaluate the effect of each action on the corresponding scenario. Based on key performance indicators for each disruption scenario, the best action is chosen. Genc [11] also uses a simulation-based technique with a stronger focus on the early detection of deviations. Therefore, he defines several critical events that should alert the decision-maker to take action. Based on a classification of events, a number of possible actions are given, which is further reduced by using several restrictions. The remaining actions are evaluated using simulation for being able to choose the best possible action for every disruption event.

Priore et al. [12] and Khosravani et al. [13] use the technique of case-based reasoning as an approach to knowledge representation in the field of machine learning. Priore et al [12] use it for real-time scheduling of flexible manufacturing systems by varying the release rules. Besides CBR they also use Support Vector Machines. Khosravani et al. [13] focus on error identification and correction in an injection molding machine. Both approaches show the potentials of knowledge representation by means of case-based reasoning, but there are no approaches for production control of the shop floor. Krumreich et al. [14] present a reference architecture for complex event processing to analyze continuous production processes in the process industry. The aim of the complex event processing is to predict the future events which may trigger further events. With this approach, the architecture of the system provides many future scenarios based on sensor data provided form the production processes. He aims to provide insights on possible process results and to simulate countermeasures to the different scenarios. The paper pursues a similar research goal but focuses only on a production process in the process industry and not on a production process in the shop floor production of discrete manufacturing as in this paper.

The current state of research shows that a lot of approaches were developed to support the production controller in disturbance management. No approach exists that is using process mining and machine learning to set-up a sustainable solution that also adapts to changes in the production system.

3. Framework for the online detection and reaction to disturbances

This section deals with the developed framework for online detection and reaction to the deviations on the shop floor. As proposed, the aim of the paper is to develop a decision support application for the production controller. This section first introduces the structure of the decision support application and then describes the important subsystems and technologies in detail.

3.1 Structure of the decision support application

The structure of a decision support application was described in section 3. In this section, we focus on the interplay of the subsystem: data component, model component, and user interface. The framework is shown in Figure 1. The decision support application will interact with the databases of the company's IT and the production controller as the designated user.

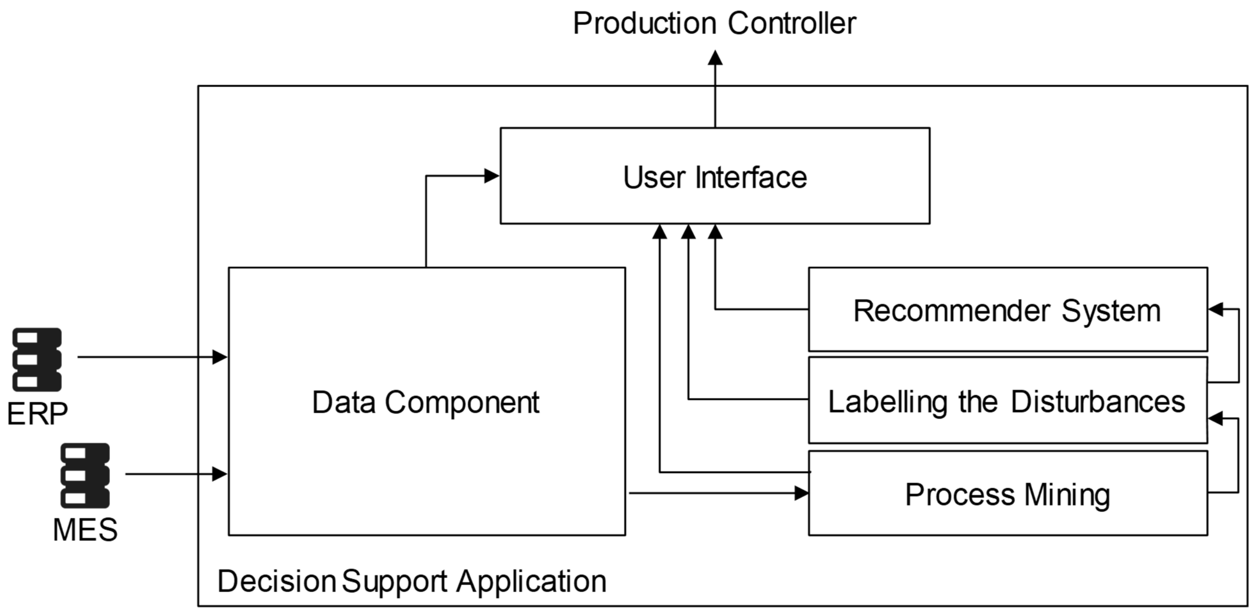

Figure 1: Structure of the framework for a decision support application for online detection and reaction to disturbances (based on [9])

The decision support application will get the feedback data from the shop floor. Depending on the IT architecture of the company this will be either stored in the Enterprise Resource Planning (ERP) system or in the Manufacturing Execution System (MES). The feedback data includes start- and end-timestamps of operations, as well as the respective resources the order used. Also, the routing will be transferred to the data component, as it will be used as the planned process. This data will be transferred to the first part of the model component, the process mining subsystem. The aim of the process mining subsystem is to analyze the actual process flow in real-time [15]. This will be used to detect and predict deviations and disturbances and to provide information on the performance of the production lines. The process mining can detect deviations regarding a violation of the process flow or a violation of operation times [15]. However, in the next phase, the process mining subsystem can be improved by adding simulation techniques, e.x., system dynamics simulation model [16] to increase the ability of the application in providing more accurate recommendations.

The performance information will be provided to the user interface while the information on detected deviations will be sent to the machine learning subsystem for labeling the disturbances. This subsystem decides whether the detected deviation is a deviation within the acceptable tolerance limits or if it is a disturbance to which a reaction should be derived. The labeling subsystem provides information about disturbed orders to the user interface. There, the production controller can give feedback if the labeling worked and can also train the system with this information after the initialization. Also, the subsystem forwards the information to the second machine learning system, the recommender system. The recommender system comprises two subparts. The first subpart is the pre-trained system, which will be set up initially to suggest reactions to the identified disturbances. The subsystem should suggest up to three countermeasures. The second part involves continuous machine learning based on the controller's feedback on the proposed measures and their effectiveness. This should enable an adaptation to the constantly changing constraints of production control. The two main advantages are the support of the production controller in the decision-making process to reduce the time to evaluate the situation and the decision making itself. The second advantage is knowledge transfer into the database. This enables intra-company knowledge storage in a field that is often driven by the experience of the employees.

3.2 Process Mining

Process mining is a relatively new research discipline which "sits between data science and data mining" [15]. Its idea is to model and analyze processes with the goal of discovering, monitoring or improving the real process based on data. The data for process mining is stored in the forms of event logs [15]. An event log is a set of traces and each trace is a sequence of events and each event includes at least case ID, activity, timestamp, and resource data. Moreover, other attributes can be added for further investigations. The case ID describes a process flow of one real case, e.g. one customer or one order in production. The activities describe the steps which the case performed from the start of the process to its end. The other fields allow further information to be included in the analysis of the process cases. For instance, performing welding (activity) for item 12 (case ID) in the production line by one of the workers Jack (resource) at 12:00:10 10.10.2019 (timestamp) is an event and if it takes ten events for item 12 to be ready in the production line then these 12 event forms a trace in the event log.

As described before, process mining can be used for discovering different process variants based on historical data. If no process model exists (neither target nor actual process), the process model can be used to derive the possible process variants and their characteristics from the data. The advantage of process mining is that all process variants and their frequencies can be displayed. This way, the most frequent process variant and the most frequent deviations can be analyzed. With conformance checking, deviations can be detected and examined using an existing process model. For this purpose, however, a process model must already exist against which the various process cases can be checked. Conformance checking enables process monitoring in the way of disturbance management. Both techniques can be used to improve processes [17].

In this framework, we perform bottleneck analysis within process mining to detect and predict deviations based on the provided data, i.e., event logs. We do so by using conformance checking to detect deviations in the flow of the activities and performance analysis [17] to detect performance deviations. The case ID will be a unique order in the Shopfloor the activities will be work steps provided in the routings.

3.3 Machine Learning

The field of machine learning is composed of methods that perform specific tasks by inferring relationships from given examples but without being explicitly programmed for the task at hand. The practical applications of machine learning systems are usually divided into a training phase in which a model is learned and a subsequent phase where the model is applied to previously unseen data or circumstances. A successfully trained model is able to generalize from the data distribution encountered in the training phase in such a way that it is also able to perform the task on the unseen data [18]. In the field of machine learning, there are different forms of learning, which are relevant to the framework of online detection and reaction to disturbances. For the two tasks of the machine learning system, the approaches are explained in the following.

3.3.1 Labeling of Disturbances

For the recommendation system labeled disturbances are needed as input data. From the process mining part of the framework, deviations will be forwarded to the machine learning system. The first task is to label the data. Therefore a case-based approach was carried out to enhance the current state of the literature on known disturbance classifications. The disturbances found by literature and interviews are classified by the 5M method [19]. This proposed classification of the disturbances builds the knowledge base for the machine learning system. Here, the task of classification will be carried out using supervised learning techniques. The user can label new data by selecting a proposed disturbance and give feedback about whether the system is correct.

3.3.2 Recommender System

The recommender system has the task to propose suitable reaction measures for the identified disturbances. In general, recommender systems suggest items to a user [20]. In this case, an item is a countermeasure to a found disturbance in the Shopfloor. The recommender system gets the classified disturbances as an input. Here, two possible approaches have been identified for building the recommender system: collaborative filtering and reinforcement learning.

Collaborative Filtering is a very promising technology for filtering data based on similarities. Collaborative filtering is often used in e-commerce. There collaborative filtering recommends items that other users bought who also bought the currently viewed item. The collaborative filtering algorithms (CFA) produce a predicted likeliness or a list of top X suggestions for the user based on the input. The input is often user-based, e.g. previous likings or other user's likings [21,22]. For the production of either a predicted likeliness or a list of top X items, collaborative filtering algorithms can be divided into two classes: memory-based CFA or model-based CFA. The memory-based approach uses the entire user database to produce the wanted output. The system searches for the nearest neighbors of the "active" user based on their history. Then the system uses different algorithms to combine users' preferences and decisions to predict the suggestion. The model-based CFA first builds a model of user ratings. One approach is the clustering model. The models structure the problem for collaborative filtering as a classification problem and therefore cluster users in classes. The active user is classified and then the particular class is analyzed and a prediction is built upon this class and not the whole user database [21,22]. In the case of the proposed framework, the user would be a production controller and the items would be disturbances and the output would be a list of possible countermeasures to handle the disturbance.

A second approach is to model the problem as a Markov decision process and subsequently solve it using reinforcement learning. A Markov decision process consists of a set of states, a set of actions, a transition function, and a reward function. Each state is a representation of the system at a particular point in time. A reinforcement learning agent interacting with the system perceives this state and performs some action to influence it. The outcome of performing a particular action in a particular state is a new state, which is determined by the transition function. After performing an action, the agent receives this new state as well as a reward to indicate how good the selected action was. While training, the agent learns a policy which determines its behavior in order to maximize its long-term cumulative reward [23]. In the use case described here, the state describes the shop floor with its disturbances, while the actions are countermeasures to the identified disturbances. Finally, the reward function implicitly defines the goals of the agent and thus needs to be carefully designed. A possible approach might be to compare the state of the system after applying the appropriate countermeasure to some disturbance with the state the system would be in had no disturbance occurred in the first place. In essence, some distance measures between states could be developed in this way such that the agent receives a positive or negative reward proportional to how much closer it moved the state of the system to the ideal state.

3.4 User Interface

The user interface is very important for a decision support application since it is the gateway to provide the relevant information to the user. Its user-friendliness and comprehensibility of the presented information improve the use and trust in the system. The user interface of the decision support application is provided as a web application. This enables the use of mobile devices so that the production controller can retrieve information even during a tour of the plant. The web interface is shown in Figure 2.

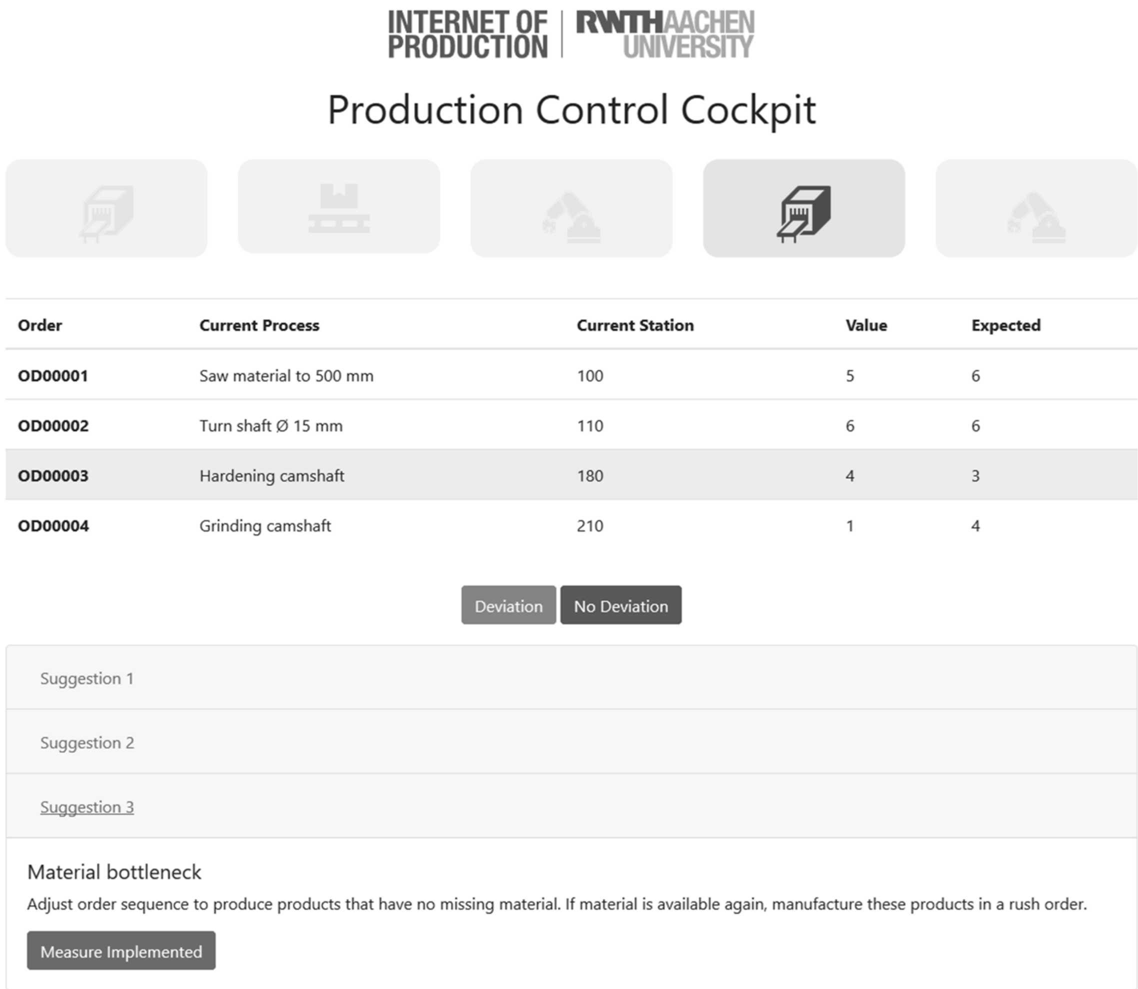

Figure 2: Interactive User-Interface for the decision support application developed to support the decision making in disturbance management

At the top, the user sees a list of all orders for which the decision support system has identified a malfunction. With the aim of enhancement techniques in process mining, the online track of the product would be available through the process. This online tracking would provide this list of orders and their possible deviations. If the user now selects a malfunction, the station is displayed in a plant layout in addition to the performance information from the process mining. The user can then also indicate whether the displayed deviation is actually a disturbance. If the production controller wants to see all open orders, he can have them displayed via a filter function and, if necessary, display the open orders as malfunctions. This information is then passed on to process mining and machine learning subsystems.

When a disturbance is selected, the user is also shown three countermeasures. The implementation of the measures lies with the production controller. Here, however, the user can specify whether he has implemented the measure and later also evaluate the effectiveness of the measure. This allows machine learning subsystems to learn continuously and improve their performance. This makes it possible to adapt to changed constraints such as new products or new routings. In addition, the user can enter new measures and thus expand the knowledge database of reaction strategies. The user can specify whether the measure is applicable to this or all fault classes.

4. Conclusion

This paper proposed a framework for decision support for a production controller in order to react to identified and predicted disturbances. Besides the framework, the general idea for the use of process mining in disturbance management has been described and the current state of the research was discussed. Moreover, process mining techniques provide enhanced analyses which makes the online track and detection of disturbance possible. In addition, the article showed how to use machine learning next to process mining to enable a recommender system to support the production controller. The framework and subsystems of the framework were described to test the system with real data. The paper at hand should form a working and discussion basis for further research in disturbance management based on the proposed system framework. In the future, this framework will be tested with simulation and real data within the research program Cluster of Excellence "Internet of Production".

Acknowledgments

Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany´s Excellence Strategy – EXC-2023 Internet of Production – 390621612.

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Biography

Markus Fischer (*1992) is a research associate at the Institute for Industrial Management (FIR) at the RWTH Aachen in the research group Production Control. He studied mechanical engineering at the RWTH Aachen University, specializing in production engineering and mechanical engineering. Currently, he is working in the research project “Internet of Production”, which aims to develop data-driven decision support systems.

Mahsa Pourbafrani (*1989) is a research associate in the Data and Process Science group of RWTH Aachen University. Her research includes simulation and what-if analysis in process mining techniques regarding the performance metrics of a process. She is also working as a scientist on “Internet of Production” project with the focus of supporting decisions in production lines using process mining.

Marco Kemmerling (*1993) is a research associate at the Institute for Information Management in Mechanical Engineering at RWTH Aachen. He studied Data Science at Maastricht University and is currently doing research in applications of data science and machine learning. Among other projects, he is working on applications of reinforcement learning within the project “Internet of Production”.

Prof. Dr.-Ing. Volker Stich (*1954) has been CEO 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 led the management of European plant logistics. In addition, he was responsible for the worldwide coordination of future vehicle development projects.