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Managing Disruptions in Production with Machine Learning

Vladimir Samsonov[1], Chrismarie Enslin[1], Ben Luetkehoff[2], Felix Steinlein[2], Daniel Lütticke[1], Volker Stich[2]

[1]Cybernetics Lab IMA & IfU, RWTH Aachen University, Aachen, Germany
[2]Institute for Industrial Management (FIR) at RWTH Aachen University

Abstract

Changing customer demands lead to increasing product varieties and decreasing delivery times, which in turn pose great challenges for production companies. Combined with high market volatility, they lead to increasingly complex and diverse production processes. Thus, the susceptibility to disruptions in manufacturing rises, turning the task of Production Planning and Control (PPC) into a complex, dynamic and multidimensional problem. Addressing PPC challenges such as disruption management in an efficient and timely manner requires a high level of manual human intervention. In times of digitization and Industry 4.0, companies strive to find ways to guide their workers in this process of disruption management or automate it to eliminate human intervention altogether. This paper presents one possible application of Machine Learning (ML) in disruption management on a real-life use case in mixed model continuous production, specifically in the final assembly. The aim is to ensure high-quality online decision support for PPC tasks. This paper will therefore discuss the use of ML to anticipate production disruptions, solutions to efficiently highlight and convey the relevant information, as well as the generation of possible reaction strategies. Additionally, the necessary preparatory work and fundamentals are covered in the discussion, providing guidelines for production companies towards consistent and efficient disruption management.

Keywords

Disruption Management; Machine Learning; Production Control; Visual Analytics; Deviation Detection; Similarity Analysis; Decision Support; Assembly; Assistance Systems; Mixed-Model Assembly

1. Introduction

"Anything that can possibly go wrong, does", is the so-called Murphy´s law. This means, that unwanted events are unavoidable and something is bound to go wrong at some point in time. These unwanted events, also called disruptions, have a negative impact on the productivity and, therefore, profitability of a production company [1,2].

In times of shrinking product lifecycles, delivery times and increasing market volatility, production companies are more prone to disruptions [3]. Decreasing product life cycles and growing customisability lead to more frequent process changes, which has a direct effect on the possibility of disruptions [4]. Adequate disruption management will help avoid stagnating or even decreasing productivity levels in the production processes in the future.

Efficient disruption management in modern production is a multidimensional problem. It requires perceiving the possible challenge, understanding it and generating a suitable, possibly novel, solution. Perception, cognition and action are the three main abilities that define intelligence in general [5]. Within the context of disruption management, perception means creating a full picture of the current production state, based on the available information. Often, available information is incomplete because of time pressure and lack of knowledge or data [6]. Cognition is related to the current production status analysis, recognition of occurred and anticipated disruptions, as well as the assessment of their probable impact and severity. Action in the context of disruption management refers to the execution of a number of activities aimed at the prevention or minimisation of negative consequences. Humans, as intelligent beings, possess natural abilities in perception, cognition and action execution and traditionally constitute the main driving force behind disruption management. However, modern production imposes new challenges beyond human capabilities. Production managers are incapable of managing the growing flow of information and often have to make decisions based only on a fraction of available information, which can lead to a suboptimal decision. A logical way to deal with the growing complexity of disruption management is the involvement of larger human teams. Nevertheless, within a team, every member has to digest the relevant information and decide upon required actions, based mostly on their personal experience and judgement. A substantial time investment is required to form a well-coordinated team with clear communication and the required levels of domain experience to make sound decisions, keeping the company's best practices in mind. Nowadays, achieving such a goal is greatly impeded by factors such as an ageing workforce, increasing staff turnover and constantly changing production environments. However, recent advances in Machine Learning (ML) provide an indication that Artificial Intelligence capable of tackling complex problems will soon be a reality [7]. This can be of great help for experts while dealing with production disruptions.

We believe that in the age of Digitization, Industry 4.0 and ML, humans will still be heavily involved in the decision-making process. However, it will consist of a hybrid workflow where part of the task will shift from a mainly manual effort to a semi-automatic or even completely autonomous approach. Smart experts and assistance systems will support the worker in making the right decisions by providing the relevant information at the perception stage, guiding the decision-making process or automating certain decisions at the cognition step and facilitating chosen actions to execute at the action stage.

In order to develop useful systems for this application area, several aspects have to be considered. In the perception stage, it is important to select, consolidate and transform relevant information from multiple sources to a form easily comprehensible by human experts. At this stage, ML can augment human intelligence with speed, consistency and precision in processing big amounts of data. Beneficial patterns in the data can be recognised that are invisible to the human eye [8]. At the cognition stage of disruption management, past and future disruptions need to be considered and evaluated. Disruptions should be classified based on their estimated negative impact. Possible mitigations, also known as reaction strategies, need to be matched to the various disruptions. Addressing different tasks at the cognition stage often requires intuitive capabilities, the ability to come up with the non-standard solutions as well as conducting complex planning. People are notably competent in this range of tasks. Nevertheless, people can still rely on ML for generation of data-driven predictions concerning the disruption risks and their severity. Additionally, human experts can be presented with recommendations to viable actions, based on similar events in the past or with the help of rule-based expert systems.

In the next chapters, we give an overview of the state of the art for both classical and ML-related approaches in the field of disruption management. Subsequently, our approach is presented, together with some related requirements and practical results based on a real use case. Finally, the conclusion and outlook finalises the paper.

2. State of the art

For the present topic, two research fields are of interest in the state of the art. Firstly, it is worthwhile to investigate the state of the art in disruption management to define its research deficits. Secondly, since disruption management is part of Production Planning and Control, the state of the art of ML in PPC is of interest.

2.1 Disruption Management

Disruptions are critical events that lead to a break in the workflow of a production process, such as machine failure, rework or missing personnel. Therefore, disruptions have a negative impact on the production system due to their substantial influence on logistical targets.

The management of disruptions as a research field already exists since the 1970s [9]. Disruption management refers to the structural and procedural organisation of all successive measures, including the elimination of disruptions, the minimisation of the consequences of disruptions and the prevention of disruptions. These three temporal organisational units are also referred to as short-, medium- and long-term disruption management [10]. In disruption management, a distinction is made between different strategies. Prevention strategies deal either with the elimination of the cause (causal strategy) or with the defence against the occurrence (defence strategy), i.e. with the avoidance of the occurrence of disruptions. Reaction strategies have two categories, namely system-oriented strategies that deal with the consequences of disruption, and reactive strategies, that adapts to the new situation resulting from the disruption. Thus, they react to disruptions that have already occurred [11].

While the first approaches in disruption management mainly dealt with the disruptions themselves and their classification [12,10], approaches in recent years focus more on data aspects and simulation [13–16]. However, especially the aspects of possible reaction strategies and the use of ML in disruption management have not yet shown satisfying results.

2.2 Machine Learning in production

Machine Learning (ML) is a subset of Artificial Intelligence (AI) and is capable of discovering underlying patterns and dependencies through examination of data [17]. ML is used across many domains of production, but is mainly used within scheduling, process planning and control [18]. In this chapter, we will cover only applications potentially related to disruption management.

One of the topics gaining attention in the research community is the use of Deep Reinforcement Learning (RL) for solving combinatorial optimisation tasks, such as scheduling [19–21]. This research direction in ML is a potentially good solution for conducting production resequencing in a flexible manner, as a response to production disruptions. Compared to classical Operations Research (OR) approaches, deep RL methods can potentially adapt to changing environments and boundary conditions by retraining without having to redesign the whole solution approach. However, deep RL methods are new. Several questions, such as explainability, validation methods, generalisation capabilities and robustness still need to be addressed before it can be deployed in real production environments [22].

Besides deep RL, unsupervised learning is another subset of ML that does not require collected data to be labelled. There are many scientific works based on unsupervised learning that elaborate on the use of clustering algorithms for automatic detection of similar products, classification of products in product families and anticipating product failures [23–25].

Another promising field is the use of Visual Analytics (VA) in production planning and scheduling. Different works propose the use of various data transformation and visualising techniques to automatically provide experts with decision-relevant information and interactively evaluate possible production scenarios [26–28].

In our opinion, the use of ML and VA approaches on the order level has not yet been discussed sufficiently in the context of disruption management.

3. Approach

The overall goal is to combine a number of ML and VA approaches to enable a data-driven prediction of production disruptions. Therefore, we introduce a practical use case with real production data used to develop and validate our approach.

3.1 Use Case Introduction

We choose a mixed model continuous assembly line producing self-checkout machines for retail to develop and test our disruption management methodology. This is motivated by the complexity of the final product. Many modules of the system, from hardware to software, are customisable to the customer needs. It leads to a vast amount of different products being produced on one line. Often, specific product configurations are produced only a few times, making erroneous planning estimations and disruptions along the assembly process more likely. Products go through a number of stations on a production line with a pre-defined cycle time. Production disruptions of any kind have to be addressed within the short period of time the product stays on a given working station. Otherwise, the assembly sequence cannot be completed and the product will have to be finished separately in the rework area. This requires additional personnel capacities, causes longer production times, higher costs and is limited to a number of products at any given time because of the rework area space and human labour constraints. Possible disruptions, if accounted for at the planning and order release stage, can be mitigated. Therefore, it is important to timely recognise and foresee disruptions.

3.2 Data

One of the most frequently used IT-systems by production companies are Enterprise Resource Planning (ERP) systems [29]. An ERP system facilitates the order processing from supplier to customer, e.g. with production planning and materials management. It leads to a certain degree of homogenisation of available data across companies. Planning data, such as the Bill of Materials (BOM) and production steps, is available for every produced order. The planning data is augmented with historical data, including disruptions in production steps, conducted rework and schedule adherence. This data is not available in every ERP system but is a crucial part in anticipating possible process disruptions [30]. The more information on circumstances, causes and impact of previous process disruptions we have, the more precise we can estimate future disruptions.

3.3 Explorative Data Analysis and General Concept

Similar orders consist of similar materials and require similar steps in the assembly process. Potentially these orders can inherit the same design flaws that make the assembly process prone to errors. Once clusters of similar orders have been identified, it is useful to know how likely each of these clusters are to be finished on time without disruptions or to be moved to the rework area. Originally, for the given use case, the product similarity is defined by four main product families that share common functional and design features. To investigate underlying structures in these product groups we use the unsupervised ML method of hierarchical clustering [31]. The features used to create

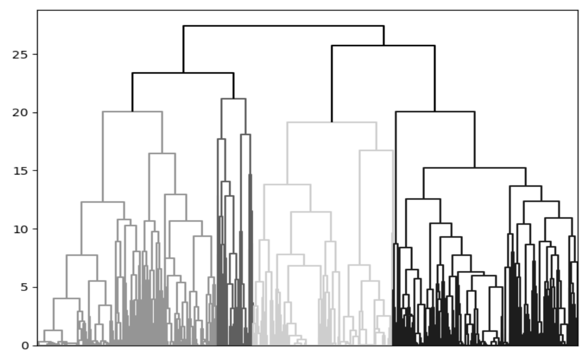

Figure 1: Four main product families represented as hierarchical clusters indicates a great amount of configuration and assembly variations

such a clustering is a combination of the materials the orders consist of and the production process steps to assemble the order. An agglomerative hierarchical clustering of the data is performed with complete linkage. Figure 1 shows the dendrogram, which is a tree-like structure, representing the results of the hierarchical clustering. This type of representation is integral to understanding how the clustering is performed. The bottom of the dendrogram represents each of the individual orders that have been produced in the past. Moving further up the tree, similar products and product clusters are linked together in larger clusters. The closer to the top the linkage occurs, the lower the degree of similarity within the cluster. At the top of the dendrogram we can recognise four horizontal lines depicting four main product families. The fact that each product family has a complex tree structure demonstrates the high level of variation in the production process. This variation is the result of high customisation possibilities for each product. Therefore, in order to approximate possible behaviours of an order based on similar orders from the past, we need to split given product families in smaller groups with higher similarity first.

Clustering helps with determining which production orders are similar, but we are interested in more than similarity. We would like to abstract this to the behaviour of the orders and would like to determine which orders will be problematic and will most likely be moved to the rework area. This extra layer of information is created by estimating the probability of any order in a cluster to be moved to the rework area, based on historical production data. With this information, the worker can undertake the necessary measures to completely avoid or minimise the impact of potential disruptions.

4. Results

The production data for the given use case contains 6153 orders. We create a one-hot encoded matrix describing all possible configurations, used parts and production steps. Every possible product in this case can be completely described by a vector of length 2462. A Principal Component Analysis (PCA) [32] is performed to reduce dimensionality. As a result, the vector describing each order is reduced to 30 dimensions that capture 93.3% of the variation in the data. It is important to generate an intuitive visualisation combining both similarity information as well as historical production data. t-Distributed Stochastic Neighbour Embedding (t-SNE) [33] is used to map the 30 dimensional production orders onto a 2D plane for the ease of visual inspection. It groups similar observations together in tight clusters while trying to pull dissimilar observations farther apart. Singular points in the 2D space represent product configurations produced only once. To ensure t-SNE visualisations depict true clusters of similar orders we use Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [34] as a validation method. Clustering methods are successfully used for detecting product families based on product similarities [23–25]. Figure 2 shows a t-SNE generated 2D map of orders. On the same visualisation, DBSCAN clusters are colour-coded. From this figure it is clear that all points assigned to the same tight cluster by t-SNE have the same colour, defined by the affiliation to the one or another DBSCAN cluster. Therefore, DBSCAN successfully clusters similar products and t-SNE represents these clusters in a 2D space.

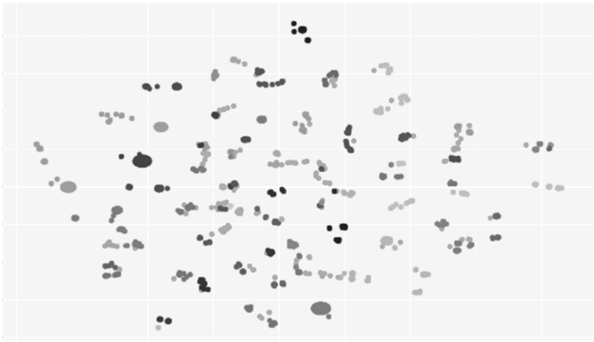

Figure 2: DBSCAN clustering of past orders represented on a 2D Map created by t-SNE

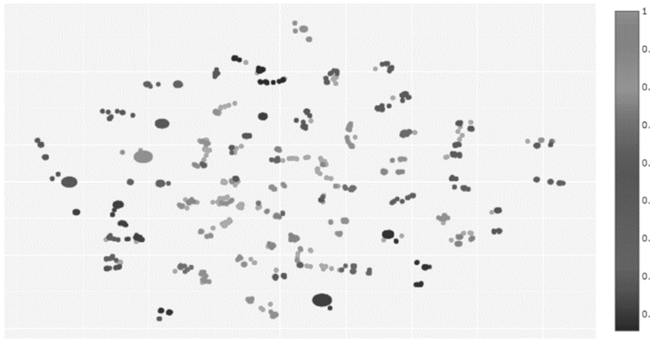

Figure 3: 2D Map of Produced Orders with Rework Ratio per Cluster

We add another layer of information to the 2D representation of all produced orders by color-coding (in this case encoded as with color gradient from black to white) according to the estimated rework ratio per cluster of similar products, which is represented in Figure 3. This allows the user to quickly see what planned orders can potentially lead to disruptions during production, because it belongs to a cluster with an estimated high rework ratio (clusters with brighter colouring) or because of a new configuration (single point not surrounded by other observations). It allows the user to prepare for possible process disruptions.

5. Conclusion and Outlook

Even in a highly automated and digitized production environment, disruptions will occur due to unforeseen failures of machines, humans or other resources. Therefore, disruption management is an important managerial task that needs to be handled with domain expertise and supported by data-driven approaches, such as ML. The presented paper introduces the concept of using ML to facilitate disruption management by identifying possible problematic orders based on historical data and through the discussion of an application use case. We used unsupervised ML to form clusters of similar product configurations, evaluate the likelihood of rework based on historical data and generate a 2D visualisation allowing to approximate how much rework planned orders are likely to require.

Building on the presented findings, the next step will be the validation of the concept. To do so, we will use data from the presented use case and implement a dashboard for the workers in the assembly line. With the dashboard, they should be able to anticipate possible disruptions and derive possible strategies on how to manage the assembly in the case of a disruption. This will serve as a starting point for the creation of an assistance system that will go a step further than solely helping to detect possible disruptions, but helping to derive possible reaction strategies. Thus, the workers need only to decide between the best alternatives, which should lead to a relief in the amount of work created by managing disruptions.

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Biography

Vladimir Samsonov (*1990) is a scientific researcher at the Institute for Information Management in Mechanical Engineering (Cybernetics Lab IMA & IfU) at RWTH Aachen University since 2017. As a part of the Digital Production Technology Research Group, he specialises on questions related to digitalisation and the use of machine learning within the context of manufacturing engineering.

Chrismarie Enslin (*1991) joined the Institute for Information Management in Mechanical Engineering (Cybernetics Lab IMA & IfU) at RWTH Aachen University in 2019. She is part of the Digital Production Technology Research Group and mainly focusses on Machine Learning and Reinforcement Learning within the field of industrial manufacturing.

Ben Lütkehoff (*1990) has been part of the Research Institute of Industrial Management at the RWTH Aachen University since 2015. He works in the department of Production Management in the group Closed-Loop Production Control, where he focusses on combining data from IT-systems with implicit knowledge of production workers.

Felix Steinlein (*1989) has been part of the Research Institute of Industrial Management at the RWTH Aachen University since 2017. His research focus lies within production planning and control, process analytics as well as enhancing operations with digitization and the use of IT-systems (MES / ERP).

Daniel Lütticke (*1984) has been part of the Institute for Information Management in Mechanical Engineering (Cybernetics Lab IMA & IfU) at RWTH Aachen University since 2016. He is leader of the Digital Production Technology group researching on advanced applications and effects of digitalisation and artificial intelligence in the field of industrial manufacturing.

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. In addition, he was responsible for the worldwide coordination of future vehicle development projects.