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Using process mining to improve productivity in make-to-stock manufacturing

Manufacturers need tools to identify issues in their value streams. Creating transparency in complex manufacturing systems is an arduous task. As a consequence, opportunities for productivity improvement often remain unnoticed.

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A central objective of productivity improvement in make-to-stock manufacturing is to increase the rate at which parts flow through a manufacturing system. Improving system flow can be achieved by reducing three fundamental roadblocks: (i) bottlenecks, (ii) process variation and (iii) non-value-adding activities (Schmenner 2012).

Manufacturers use process mapping methods to understand the current state of their operations. Many existing methods, such as value stream mapping, seek to identify improvement potentials by first visualising the processes. This provides a snapshot of the process flow, based on which manufacturers can analyse inefficiencies at a given point in time. However, because such process mapping tools are static, they are less effective when the process flows dynamically change over time. Moreover, existing manual methods are resource intensive, which limits their applicability in situations with high process complexity. At the same time, the increasing amount of data that is captured in the era of Industry 4.0 offers new opportunities to explore actual process flows in reality. This motivates the use of data-driven methods to exploit hitherto untapped potential for productivity improvements.

This paper overcomes the limitations of existing methods for process mapping in manufacturing by proposing the use of process mining. Process mining is a recent development in information systems research that models process flows based on event log data (van der Aalst 2016). In contrast to manual process mapping, process mining allows analysing process flows dynamically and identifying non-value-

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adding activities in an automated manner/ For this reason, process mining is particularly suitable for discovering process deviations and identifying factors that negatively affect productivity.

Theoretical background

Industry 4.0 offers promising opportunities for improving manufacturing operations. Starting as a state policy to innovate manufacturing in Germany, Industry 4.0 has become an important field for both research and practice. The term bundles various emerging technologies that turn factories into cyber-physical systems generating large amounts of data. In order to take full advantage of these data assets, they must be ‘mined’ and analysed. However, many manufacturers still struggle to leverage their data for improvements. Xu, Xu, and Li (2018) propose four key challenges to firm-level Industry 4.0 deployment, namely technology, collaboration, management, and implementation. This research primarily focuses on the last of these, thereby guiding manufacturers with a concrete procedure for improving their productivity through process mining.

Process productivity

In make-to-stock manufacturing, productivity can be defined by the rate at which units flow through a system – its throughput rate. Improving the flow through a manufacturing system requires the identification and reduction of bottlenecks, process variation and non-value-adding activities (Schmenner 2012).

The bottleneck is the process that constrains the throughput the most (Wiendahl and Hegenscheidt 2002). Several bottleneck detection methods have been proposed. For instance, Roser, Lorentzen, and Deuse (2015) perform a ‘bottleneck walk’ to identify the bottleneck by shop floor observations of inventory and process starvation. Other methods include the statistical computation of mean process cycle times or waiting times (Betterton and Silver 2012; Hopp and Spearman 2008; Scholz-Reiter, Hildebrandt, and Tan 2013). A limitation of traditional bottleneck detection methods is their inability to cope with dynamic high-mix production environments.

Process variation is the second concept that affects the productivity of a system. Queuing theory shows mathematically that increased variation reduces the productivity of a process. Processes can vary in many different attributes, such as process cycle times, processed materials, operator decisions, operator movements or machine parameters, among others.

Finally, the concept of non-value-adding activities, so-called waste, is central to productivity. The more waste is inherent in a system, the less productive it will be. Waste reduces both the swiftness and evenness of processes. Examples of waste are unnecessary transportation, inventory, motion or waiting, overproduction, overprocessing and the production of defects. Lean management sets a focus on reducing the different types of waste from a process. However, these attempts to reduce waste are often limited to single processes and do not consider the whole value stream. A popular procedure to map and analyse waste in a system is Value Stream Mapping (VSM; Rother and Shook 2003). However, VSM is a static snap-shot method that requires extensive effort to create and maintain.

Process mining

By enabling a low-effort automatic mapping of actual process flows, process mining offers the potential to overcome the challenges mentioned above (cf. van der Aalst 2016). The goal of process mining is to discover the actual process flows that were observed within a system. Essentially, it bridges the gap between data science and process science. In contrast to traditional management tools such as business process management, process mining allows for the dynamic analysis of the actual process flows that were executed.

Process mining utilises event log data that is recorded when executing a process. These event logs can consist of different features describing the context of the events recorded. The minimum required features include a case ID, the description of an activity and a timestamp. The case ID is a unique identifier referring to a single instance, such as a booking number for a flight. The activity describes an action that has been performed, such as check-in or boarding. The timestamp describes the specific time the activity has been performed. Based on this input, process mining generates a process model that reproduces the observed process flows. Note that the above features only represent the minimum information required. More information can be mined, such as the resource with which the process was performed or the cost of the process.

Several algorithms for extracting a process model from an event log exist. The underlying principle of such an algorithm γ is to map event log data L onto a Petri net γ (L). Thereby, the net represents the different traces observed in the event log (van der Aalst 2016). One of the first process mining algorithms was the alpha miner, but it is vulnerable to missing data. To date, common process mining algorithms are the heuristic miner, the inductive miner, the fuzzy miner and variations of the alpha miner.

Process mining also offers the opportunity to analyse the conformance of the observed processes by comparing the as-realised process flows with the as-designed process model. The as-designed processes can be modelled, for instance, by applying the standards provided by Petri nets or business process model notation (BPMN). Here, replay fitness is a common measure to quantify the conformance. It evaluates how well the as-designed process model can reproduce the actual cases in the event log (i.e. as-realised). Other measures include precision (examines underfitting of the model) and generalisation (examines overfitting of the model).

There are several generic methods for the implementation of process mining. One example is the L* lifecycle model, which consists of the following five stages: plan and justify, extract, create a control-flow model, create an integrated process model and operational support (van der Aalst 2012). Knoll, Reinhart, and Prüglmeier (2019a) propose a four-step methodology for multi-dimensional process mining. This methodology is based on the Process Mining Project Methodology (PM2), which provides a generic method for a process mining project (van Eck et al. 2015). However, to date, there is limited evidence for the utility of the proposed methods for productivity improvement within manufacturing.

In recent years, the amount of data collected in manufacturing has increased exponentially. Consequently, many manufacturing companies already collect relevant process data in their information systems (e.g. enterprise resource planning, manufacturing execution system, warehouse management system). Process mining can help exploit these data assets by creating transparency about the real-world processes and allowing for subsequent analysis. However, much of the research on process mining has focused on the service industry (e.g. insurance, banking, healthcare), and studies in manufacturing settings are rare.

Evaluating the potential of process mining in manufacturing can benefit from an intervention in a real-world factory. This paper provides a holistic overview of how process mining can improve productivity in make-to- stock manufacturing.

Proposed procedure

This section presents a three-phase procedure for using process mining to improve productivity in make-to-stock manufacturing. Following Schmenner (2012), the procedure addresses the three components that affect the flow of a manufacturing system, namely bottlenecks, process variation and non-value-adding activities. The proposed procedure utilises event logs typically stored in manufacturing information systems to map the actual process flows in a factory. Unlike manual process mapping, the proposed procedure allows analysing process flows dynamically and discovering non-value-adding activities in an automated manner. This way, processes that constrain productivity can be identified both effectively and efficiently.

Problem statement

The goal of this research is to improve the productivity of manufacturing systems by maximising throughput.

Following Little’s law, the throughput rate is inversely proportional to the average time a part spends in a system (Little 1961). Therefore, to optimise the throughput of a manufacturing system, it is necessary to minimise the average throughput time.

As discussed, the throughput time in a manufacturing system is affected by bottlenecks, process variation and non-value-adding activities (Schmenner 2012). Reducing throughput times requires an understanding of how single parts actually flow through a manufacturing system. Traditional methods for process mapping are mostly manual and lack the ability to model the actual process flows dynamically; that is, they cannot map how the process flows change over time. The proposed procedure based on process mining addresses these limitations by automatically extracting an as-realised process model from event log data.

Formalisation of procedure

The proposed procedure consists of three phases: (i) map, (ii) analyse and (iii) improve (Figure 1). In the first phase, the user defines the as-designed process model and applies a process mining algorithm to extract the as-realised process model from an event log. The as-designed process model describes the intended flow through a manufacturing system, whereas the as-realised process model reproduces the actual flow through a manufacturing system. In the second phase, the user analyses wasteful activities through the as-realised process model and compares the actual process flows with the as-designed process model. In the third phase, the user determines improvement actions based on the previous phase and updates existing deviations in the master data. The three phases should be repeated routinely.

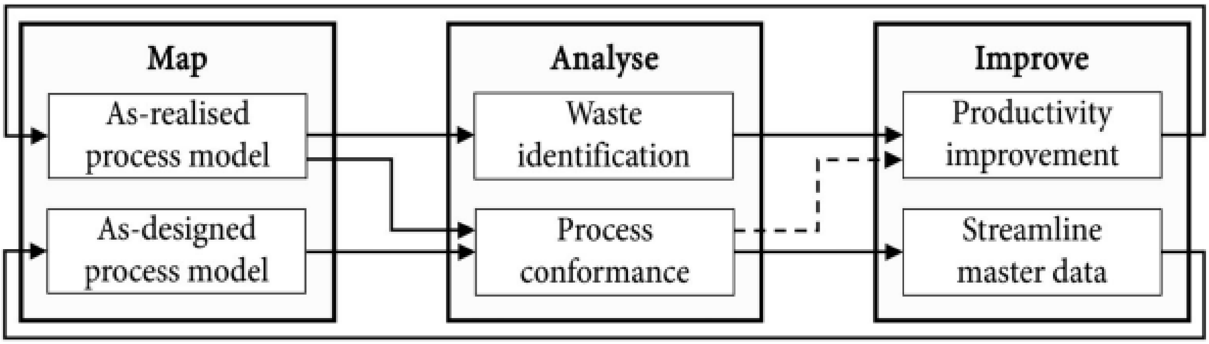

Figure 1. Process mining procedure for productivity improvement in manufacturing

Phase 1: map. The proposed procedure utilises the standard Business Process Model Notation (BPMN) to derive the as-designed process model. This process model is based on existing work plans with master data and shop floor observations. The data input for the as- realised process model is given by case IDs, activities and timestamps. In a manufacturing context, the case ID can describe a unique identifier for a specific part produced in the factory. The activity variable indicates which specific process was performed on the part. The timestamp indicates when a process started, finished or both. This information is typically stored in manufacturing information systems and must be pre-processed according to the format required for process mining (see Table 1). The resulting event log specifies what process has been performed on which part at a given time. Based on this input, the as-realised process model is constructed automatically by applying a process mining algorithm. The output provides a dynamic representation of as-realised process flows. Both the as-designed and as-realised process models serve as a basis for the subsequent analysis phase.

Table 1. Format of exemplary event log for process mining.

Case ID	Activity	Timestamp	...
EX001	Moulding	2021-01-25 07:58:20h	...
EX001	Assembly	2021-01-25 08:05:03h	...
EX002	Moulding	2021-01-25 08:32:19h	...
EX001	Packaging	2021-01-25 08:45:37h	...
...	...	...	...

Phase 2: analyse. The as-realised process model provides insights into how single parts flow through a manufacturing system. This allows identifying bottlenecks, excess inventory, and unnecessary

material movement. Bottlenecks can be located by assessing the cycle times of processes. Formally, a bottleneck is located at the process j for which the cycle time CT_j is maximised.

Unlike manual process mapping, process mining enables the investigation of cycle times dynamically over time. This way, the proposed procedure also takes shifting or variant-specific bottlenecks into account. Excess inventory can be uncovered by analysing the reconstructed flows to and from single processes, whereas unnecessary material movements are inferred via deviations from the intended process flow.

To evaluate how well the intended process flow conforms to the actual sequence of activities, the proposed procedure estimates the replay fitness of the as-designed process model. Let σ describe a trace in the event log L (i.e. a sequence of activities) and N define the as-designed process model. Then, the trace-level replay fitness can be computed via

$$fitness(\sigma, N) = \frac{1}{2}\left(1 - \frac{m}{c}\right) + \frac{1}{2}\left(1 - \frac{r}{p}\right), \tag{1}$$

where m corresponds to missing, c to consumed, r to remaining and p to produced tokens in the model (van der Aalst 2016). Tokens are basic elements of the process model indicating whether an activity was recorded in the sequence defined (van der Aalst 2016). To obtain a conformance measure for all observed traces, the replay fitness is computed at the event log level. A replay fitness of 1 (i.e. no missing or remaining tokens) suggests that the actual process flow entirely conforms to the as- designed process model. In contrast, a replay fitness of 0 (i.e. all tokens are missing or remaining) indicates the as-designed process model cannot describe the actual process behaviour at all. For more details on conformance checking, see van der Aalst (2016).

Phase 3: improve. Based on the previous phase, two different types of actions can be taken. First, the process conformance provides information that streamlines the as-designed master data. Second, the findings derived by the waste analysis are used to enhance the productivity of the real manufacturing system. Ultimately, both actions inform the first phase of the proposed procedure by updating the as-designed and as-realised processes.

Discussion

Comparison to existing methods

Modelling the process flow through VSM – one of the most popular process mapping tools – would only capture the average cycle times of processes. However, it would not have been possible to directly analyse when and why specific problems occur. Furthermore, in the case that the cycle time measurements are performed directly on the shop floor with human observations, as originally proposed by Rother and Shook (2003), the data collection is restricted to a limited observation period. Provided the VSM is conducted during a time- frame where certain time-dependent phenomena were not observed (e.g. material waiting times due to shift changes), outlier events would have gone unnoticed. Similar limitations also apply to other static mapping methods, such as bottleneck walks (Roser, Lorentzen, and Deuse 2015).

The proposed procedure also allows for analysing all the different routes that all parts have taken through the manufacturing system. Again, traditional process mapping techniques do not capture the holistic and dynamic material routings. Process mining enables to identify and follow the paths of specific parts that reduce throughput. Note that the actual process flows could also not have been mapped by available business intelligence solutions, which focus on reporting and visualisation of performance measures rather than the analysis of flows (cf. van der Aalst 2016).

Challenges related to implementation

The presented work promises widespread applicability in manufacturing settings with highly automated data capture and unknown or moving capacity constraints. However, although the potential of the proposed procedure has been demonstrated, there are several challenges related to its implementation.

One general challenge is related to the identification of suitable business cases. This challenge is omnipresent in the literature on digitalisation of manufacturing. For companies the establishment of data capture technologies can be a major inhibitor. In addition, process mining software must be acquired, often at a considerable cost. Identifying a positive business case before investments may be difficult in some settings.

A second challenge is that data in manufacturing are often incomplete and stored in different formats and locations. The accuracy of the extracted process models strongly depends on the completeness of event logs. Too many missing observations can lead to incorrect conclusions because the modelled process flows do not match the actual process flows. For this reason, process mining is more suitable for manufacturing settings with a high degree of automation. Although the amount of data that is generated in manufacturing is increasing drastically, it is often not readily available in a suitable format (Xu, Xu, and Li 2018). Therefore, pre-processing data for analyses can involve considerable manual effort. Furthermore, the required data might not yet be captured from the physical process. In manufacturing, it is costly to replace older machines having limited sensory abilities. Hence, many manufacturers have incrementally introduced automated data capture by retrofitting existing production lines. However, despite the highly automated nature of the empirical setting, the authors encountered lines that did not yet have readers to track the entire flow of the material. This might limit the scope of analysis and improvement actions that can be derived from process mining.

A third challenge arises when one aims to analyse the flow of several products that are assembled together, which requires merging case IDs. This is non-trivial and a current field of research for the further development of process mining algorithms. This is particularly challenging for manufacturing processes, where the level of the analysed entity changes – for instance, when a manufacturing order consists of multiple assembly orders for multiple products, or when parts are looping back to previous processes.

Mining data on the serial number of the product already reveals valuable insights for productivity improvement within manufacturing.

A fourth challenge is that process mining can require an extensive coordination effort between process owners. This is particularly the case for long value streams. Process understanding is necessary to suggest suitable improvement actions. Although the process mining algorithm extracts the process model automatically from the event logs, the proposed procedure involves manual analyses. Notably, the third phase of the proposed procedure may require profound domain expertise to address the underlying reasons for existing deviations.

A fifth challenge is maintaining data management discipline. When collecting and storing data in centralised systems, communication about which data to store in what way is crucial. Process mining supports manufacturers with this issue by providing simple and clear data requirements. It becomes evident for the process owners which data is relevant but missing. These instructions are important to guide data acquisition on the shop floor.

Conclusion

Traditional process mapping requires extensive manual effort and provides only a static overview of a manufacturing system. The dynamic discovery of actual process flows in factories enables the identification of capacity constraints, process variability and waste. For this purpose, this paper provides insights into how process mining can be used in manufacturing, what benefits it can provide and what specific challenges arise.

Questions

1. **What are the managerial problems the article examines?**
2. **What is the connection between process productivity and process mining? Please, explain your ideas with an example.**
3. **How the process mining procedure for productivity improvement described in the article might be applied to a company? Please, provide an example.**
4. **Imagine yourself being a manager responsible for Production System Development in a company. What lessons would you learn after reading this article?**