Application Fields and Research Gaps of Process Mining in Manufacturing Companies

Simon Dreher[1], Peter Reimann[1,2], Christoph Gröger[2]

Abstract: To survive in global competition with increasing cost pressure, manufacturing companies must continuously optimize their manufacturing-related processes. Thereby, process mining constitutes an important data-driven approach to gain a profound understanding of the actual processes and to identify optimization potentials by applying data mining and machine learning techniques on event data. However, there is little knowledge about the feasibility and usefulness of process mining specifically in manufacturing companies. Hence, this paper provides an overview of potential applications of process mining for the analysis of manufacturing-related processes. We conduct a systematic literature review, classify relevant articles according to the Supply-Chain-Operations-Reference-Model (SCOR-model), identify research gaps, such as domain-specific challenges regarding unstructured, cascaded and non-linear processes or heterogeneous data sources, and give practitioners inspiration which manufacturing-related processes can be analyzed by process mining techniques.

Keywords: Process Mining; Application; Production; Manufacturing; SCOR; Literature Review

1 Introduction

Manufacturing companies are facing global competition and increasing cost pressure due to new competitors in the proceeding globalization of markets. In order to ensure future competitiveness, companies need to optimize their costly manufacturing-related processes regarding effectiveness and efficiency [BPR16]. This process optimization first requires a profound understanding of one's own manufacturing processes. However, this knowledge and transparency is often not sufficiently available in companies as defined process models in manufacturing often only represent an idealized image of reality or are not transparent [EAW15]. Hence, process owners, e.g., production managers, cannot implement process optimizations to be able to meet targets set by the management of the company [EAP15]. Companies are increasingly using information systems in manufacturing such as Enterprise Resource Planning (ERP) or Manufacturing Execution Systems (MES) to plan and control processes and resources. As a result, large amounts of process-related data are collected and stored in database systems, data warehouses, or data lakes [Gr16]. However, data are available in such large quantities that the results of conventional methods (e.g., Reporting, Online Analytical Processing (OLAP), Value Stream Mapping), which work with aggregated

[1] Graduate School of Excellence advanced Manufacturing Engineering, University of Stuttgart, Nobelstr. 12, 70569 Stuttgart, Germany, simon.dreher@gsame.uni-stuttgart.de, peter.reimann@gsame.uni-stuttgart.de
[2] Institute for Parallel and Distributed Systems, University of Stuttgart, Universitätsstraße 38, 70569 Stuttgart, Germany, christoph.groeger@ipvs.uni-stuttgart.de

 doi:10.18420/inf2020_55

data, are often not as detailed and precise as necessary. Hence, these methods are not able to provide the highly needed process knowledge and transparency [VW04, Va16] or require a high amount of manual effort for data integration and analysis [KRP19].

In this context, process mining has developed in recent years and has established itself as an independent research discipline [Va16]. By a process-oriented view on raw data, process mining constitutes an important approach to gain a profound understanding of the actual process execution. This process-oriented view is created by applying data mining and machine learning techniques on event data. Using process mining to explore the event logs related to manufacturing processes is a promising way to gain the necessary process knowledge and transparency in order to pave the way for process optimizations and future competitiveness [Va16]. In recent years, the number of publications on process mining in the academic field has increased significantly. This is underpinned by literature reviews on the application of process mining in various domains [Da18, Ga19]. These especially show that process mining has so far been less researched for the manufacturing industry compared to other domains. However, the ongoing digitalization in line with Industry 4.0 has significantly improved the data basis in manufacturing and makes this domain along with its process-oriented characteristics predestined for the use of process mining.

Hence, this paper provides a systematic literature review to contribute to the stream of literature focusing on the domain-specific application of process mining. We survey various use cases for analyzing manufacturing-related processes using process mining and identify research gaps for future directions in this relatively new field of study. Note that we do not want to make a statement about the general importance of process mining for manufacturing and especially not about its importance compared to other, specific analytical tools from manufacturing literature, such as lean production methods or value stream mapping. Therefore, our contribution is intended mainly as an analysis of the application of process mining in manufacturing and of associated research gaps. In order to classify the identified use cases, we propose the SCOR-model [HSW04]. By an operational process perspective, the SCOR-model integrates concepts of business process re-engineering, benchmarking and process measurement into one framework. It has become the de-facto standard for defining process types in operations management [HSW04] and is consequently adopted for this review. As the SCOR-model is implemented in many companies, our classification of use cases gives practitioners inspiration which manufacturing-related processes can be analyzed by process mining techniques.

The remainder of the paper is structured as follows: Section 2 describes theoretical background. In Section 3, the literature selection process is clarified. Section 4 outlines the identified use cases, while Section 5 discusses research gaps. Section 6 summarizes with a conclusion.

2 Theoretical Basis

This section outlines the fundamental basics of the SCOR-model and process mining.

2.1 SCOR-model

The SCOR-model was first developed by the Supply Chain Council in 1996 and has been revised continuously [HSW04, Zh11]. The SCOR-model basically differentiates six level 1 process types: Plan, Source, Make, Deliver, Return and Enable [HSW04]. These process types represent potential application fields of process mining for our literature review. So, we give a brief overview on these process types in the following. The Plan process contains all activities that balance demand and supply in order to develop a course of action which best meets sourcing, manufacturing and delivery requirements [Zh11]. The Source process describes activities that procure and issue materials needed to produce the planned demand. The subsequent Make process includes all activities that transform material to finished products and is considered to be the core process of the model [Zh11]. The activities of the Deliver process provide the finished products to retailers and/or end-consumers [HSW04]. The Return process encompasses activities managing the reverse flow of used products and materials back to the manufacturing company [Zh11]. The Enable processes support the realization and governance of the other process types. Hence, they interact with the HR, IT and Financial department [HSW04].

2.2 Process Mining

According to van der Aalst, „the idea of process mining is to discover, monitor and improve real processes [. . .] by extracting knowledge from event logs readily available in today´s systems.“ [Va16] It constitutes an important data-driven approach applying data analytics and machine learning on event data. Process mining can be distinguished from traditional business process management (BPM) by the fact that BPM methods usually allow for identifying a process model by means of expert interviews, and not based on data. Nevertheless, the application of process mining methods and BPM is not an either/or decision, but process mining establishes a connection between data science and BPM or process science [Va16]. Process mining can basically be applied for all kinds of processes. In doing so, data from one or more IT systems (e.g., ERP, MES), is extracted into an event log representing the history of process executions [Va16]. To analyze the event log data, various algorithms can be used [Va16]: e.g., α-algorithm, heuristic miner, genetic miner, inductive miner and the fuzzy miner. However, the α-algorithm has a lot of shortcomings, like problems with noise or complex routing constructs. It is therefore not seen as one of the main algorithms used to analyze event data [Va16]. Instead, the inductive miner is mainly used and seems to provide the best results [NE19, Va16]. The first academically developed process mining software tool “ProM” was introduced in 2005 and has been continuously developed since then [Va16]. In the past years, commercial software vendors added process mining functionality to their tools as well [Va12a]. According to van der Aalst [Va16], three categories of process mining may be distinguished: process discovery, process conformance and process enhancement. The aim of process discovery is to convert event log data into an initial process model describing how actual processes have been executed [Va12b]. So, this initial process model represents the order of individual process steps, including possible branches and loops between the steps. The aim of process conformance is to compare the actual process execution with a predefined process model in order to check whether defined process steps are carried out properly [Va12b]. Finally, the goal of process enhancement is to extend a previously defined process model or to optimize the process, e.g., with regard to bottlenecks and resource utilization [Va12b].

3 Methodology

To provide an overview of applications of process mining in the manufacturing field, we conducted a systematic literature review following the steps proposed by Thomé et al. [TSS16]. We defined keywords according to the main objective of the paper and then combined these keywords in the search string ("process mining" AND ("manufacturing" OR "production")). We then used this search string to identify relevant articles and conference papers in six different databases: SpringerLink, IEEE Xplore, ScienceDirect, Web of Science, Emerald Insight and Academic and Business Source Premier. We retrieved 361 articles by searching titles, abstracts and keywords of all publications within these databases with the search string. Subsequently, we removed duplicates (to reject 53 articles) and then screened titles, abstracts (to reject 281 articles) and finally also full texts (to reject 4 articles) based on the following inclusion and exclusion criteria.

Inclusion criteria:

- Full text of the paper is electronically available
- Paper focuses on the application of process mining for process analysis by conducting a case study

Exclusion criteria:

- Paper is not written in English or German
- Paper is published outside peer-reviewed journals or conference proceedings
- Paper references process mining solely in its introduction or only as future research directions
- Paper is not focused on process mining, e.g., mining metal

Through this procedure, we identified 23 relevant articles and conference papers.

Note that not every paper that analyzes process mining explicitly uses the keywords we used in our search string mentioned above. So, there might be a few relevant articles that we possibly did not identify, as they use other related keywords. The keyword “process mining” also limits the covered time period, since this term for process-oriented mining approaches had not been used until van der Aalst coined this term in 1998 [VW04]. Nevertheless, we decided to use the keyword “process mining” in the search string, since process mining has meanwhile established itself as an independent research stream. So, the keyword “process mining” is sufficient to identify a vast amount and also the most important papers regarding the application of process mining in manufacturing.

4 Results

The distribution of the publications over years ranges from 2009 to 2020 and shows a strong increase in 2017. This supports the proposition that digitalization and Industry 4.0 improved the data basis in manufacturing in recent years making the use of data-driven approaches like process mining valuable. In the following, we classify the identified literature that represent potential application fields for process mining according to the six process types of the SCOR-model. Table 1 provides an overview. As the Make process is considered to be the core process, most studies have been identified here. No articles can be assigned to the Return process.

Tab. 1: Literature assigned to the SCOR-process-types and to the process mining categories

	Process Discovery	**Process Conformance**	**Process Enhancement**
Plan	[Er18], [NE19]	[Ji18]	[Ji18]
Source	[BLP17], [RC09], [RC17]	[EAP15], [EAW15]	[EAW15], [RC09], [RC17]
Make	[BPR16], [DSK17], [IB18], [Me17], [NWD19], [RC09], [Ro09], [RAB18], [Ru18], [TS16]	[Na17], [Pi17], [RAB18], [Ro09]	[AB20], [Pa15], [RAB18], [RC09], [Ro09]
Deliver	[RC09]	[Pa13]	[RC09]
Return	-	-	-
Enable	[Ro19]	-	-

Process mining in the Plan process

Three studies can be assigned to the Plan process [Er18, Ji18, NE19]. In order to efficiently generate manufacturing plans, companies make use of IT systems (e.g., ERP systems), which create corresponding planning drafts based on capacities and demand. High uncertainty about the future forces companies to frequently modify the plans [Mu06]. This so-called "nervousness syndrome" causes the "bullwhip effect" in supply chains, which has been analyzed predominantly using system dynamics or mathematical models [Mu06]. Er et al. aim to investigate the effects of this syndrome on process level by applying process discovery on ERP data [Er18]. The results show amongst others that the use case company changed 31% of its plans. Thereby, the "nervousness syndrome" could be proven at process level by using process mining [Er18]. As manufacturing plans are generated for different purposes, planning processes also show diverse characteristics. Consequently, each kind of planning process may require the usage of different existing process mining algorithms. Nuritha/Er [NE19] apply five algorithms to the use cases of two different planning processes. By extracting ERP data for each process, Nuritha/Er suggest due to their performance comparison that the genetic and inductive miner are suitable for the considered use cases of planning-to-stock processes, and that the inductive miner is most appropriate for the use case of planning-to-export processes. However, this claim also needs further validation [NE19]. Since the concepts of self-organizing manufacturing systems indicate reductions in planning efforts, little knowledge exists on the quality of the self-planned and self-executed manufacturing processes [Ji18]. Jimenez et al. [Ji18] apply conformance checking and enhancement for the diagnosis of self-organizing manufacturing systems. They show improvements in the function of those systems by permitting efficient and smooth reactions to perturbation events. So, process mining can support evaluations of plans generated by self-organizing manufacturing systems [Ji18].

Process mining in the Source process

Overall, four studies may be assigned to the Source process [RC17, EAP15, EAW15, BLP16]. R'bigui/Cho [RC17] demonstrate the usability of process discovery and enhancement for sourcing processes in heavy manufacturing industries. Er et al. [EAP15] address the problem of disruptions and downtimes in manufacturing due to defected or missing material. They apply conformance checking to the process handling incoming material at warehouses based on ERP data. The results show that the actual process highly conforms to the predefined standard. However, in case of failed quality checks, additional manual tests need to be done delaying the entire process. The analysis also found the single sourcing strategy to be critical [EAP15]. The storing and issuing of material to the manufacturing line is considered as one of the critical processes in sourcing. Er et al. [EAW15] analyze material movements in warehouses to carry out process conformance checking and enhancement. The conformity check indicates that additional, previously not defined process steps are carried out, while others are skipped presumably for time reasons. Some materials cause disruptions due to quality defects, even though the quality was checked before. The analysis reveals that materials stored in high racks are particularly prone to quality issues. Hence, this process step can cause damage and has to be optimized. Finally, a dotted chart analysis of individual process steps states that the First-In-First-Out (FIFO) rule is not maintained [EAW15]. As sourcing processes are characterized by high frequency of changes and fluctuations, defined process models need to be updated continuously. Becker et al. [BLP17] propose a process maintenance concept based on process mining. Process mining acts as an enabler to automatically create process models and this way replaces manual paper and pen modeling. However, challenges exist as standard software cannot handle the heterogeneous data sources [BLP17].

Process mining in the Make process

Thirteen and hence the most amount of articles may be assigned to the Make process [Ro09, Pa15, BPR16, TS16, DSK17, Na17, Me17, Pi17, IB18, RAB18, Ru18, NWD19, AB20]. Rozinat et al. [Ro09] show one of the first applications of all three process mining categories by analyzing the test phase of wafer steppers. Park et al. [Pa15] demonstrate the use of process enhancement for workload and delay analysis in make-to-order manufacturing. Dišek et al. [DSK17] discover the control flow and other parameters of the manufacturing process of transmission parts in the automotive industry. Ribeiro et al. [RAB18] use process conformance and enhancement to analyze unsatisfactory performance levels approached in the referred process. Based on the analysis results, they propose adjustments to the "L*life-cycle model" methodology developed by van der Aalst [Va16]. Bettacchi et al. [BPR16] compare the application of five algorithms on an interlinked manufacturing process. They show that the inductive miner is best-suited for process discovery in their use case. Semi- and unstructured processes are addressed by Meincheim et al. [Me17], who combine the inductive miner with trace clustering to discover process variants based on MES data. This approach seems promising for analyzing performance issues in unstructured processes. Intayoad/Becker [IB18] and Natschläger et al. [Na17] show that unstructured processes are often accompanied with heterogeneous data sources. Hence, Intayoad/Becker apply a Markov chain as a sequence clustering technique for the data processing steps based on MES data [IB18]. A comparison of the results with and without Markov chain shows an improvement of the discovered process model quality by the indicator of replay fitness. They conclude that involving experts with domain knowledge is crucial for successful process mining in manufacturing [IB18]. Natschläger et al. check the conformance of two manufacturing processes using process mining based on ERP data [Na17]. They propose a new procedure to extract, load and transform data from heterogeneous sources, which can also be applied in other application domains [Na17].

Most mentioned studies use ERP data. In contrast, Altan/Birgün [AB20] apply process enhancement to the manufacturing process of propeller shafts using machinery data. They use process mining to evaluate lead times and to improve the machining process [AB20]. Others studied the use of process mining for Make support processes and side aspects. Tu/Song [TS16] propose a concept to analyze and predict manufacturing process costs based on process enhancement. Therefore, they extend the event log by the costs of each activity in a process. They demonstrate the concept by analyzing a manufacturing processes of jeans [TS16]. Pika et al. [Pi17] provide insights on the usability of process mining for checking conformance of safety processes in the manufacturing area [Pi17]. Ruschel et al. [Ru18] apply process discovery for maintenance inspections of machines and equipment providing better support to managers in scheduling activities [Ru18]. Nagy et al. [Na17] use real-time process mining to detect early deviations in a manufacturing process. They show that real-time process mining can speed up the process of detecting potential sources of defects and thereby reduce the number of faulty products.

Process mining in other process types

The study of Paszkiewicz [Pa13] may be assigned to the Deliver process. Paszkiewicz uses conformance checking to analyze the outbound logistic process of delivering products to the company´s customer. The results show that rules, e.g., FIFO, are not obeyed by employees, and further analyzes indicate an ineffective configuration of the warehouse [Pa13]. The study of Roldán et al. [Ro19] can be assigned to the Enable process. The authors investigate how a training system for industrial operators in assembly tasks may benefit from process discovery and virtual reality. Their results show that the automatically retrieved process models can help in teaching new employed machine operators in an efficient way [Ro19]. Finally, R'bigui/Cho [RC09] examine a customer order fulfillment process of a heavy manufacturing company using process discovery and enhancement. This study spans several process types (Source, Make and Deliver processes) and, thereby, constitutes the only study, which analyzes an end-to-end process.

5 Research Gaps

The conducted literature review surfaces a variety of process mining applications in manufacturing companies. However, there still exist research gaps, which we derived from the results of our study and which we explain in the following.

Consideration of process types and mining categories

As shown in Table 1, most studies explore the process type Make, while the Plan and Source processes receive some attention. However, the Deliver and Enable processes are considered too rarely so far, while the Return process is even not covered at all. This Return process is however of particular interest, since it is becoming crucial in the course of an increasing circular economy in manufacturing. So, one research gap is to identify and analyze additional possibilities to use process mining for Deliver, Enable, and especially Return processes. Furthermore, only one study analyzes end-to-end processes [RC09]. As the optimization of end-to-end processes has a greater impact on efficiency improvements, future research should investigate the usefulness of process mining on a larger scale for these end-to-end processes. Moreover, the results show that most studies aim to discover process models (14 of 23 articles), while less studies check conformance (8 of 23 articles) or enhance (8 of 23 articles) existing models. Only 6 of 23 articles combine those approaches [EAW15, Ji18, RAB18, RC09, RC17, Ro09]. Yet, conformance checks and process enhancement are of utmost importance for companies in order to keep their manufacturing processes compliant and to optimize them. Hence, future research should especially focus on conformance checking and process enhancement.

Selection of process mining algorithms for given use cases

There is little knowledge on how to select the right process mining algorithm for a given manufacturing use case [NE19]. For instance, it would be valuable to know which process mining algorithm is suitable for each SCOR-process-type. Thereby, future work is to develop a selection framework which assigns algorithms to a SCOR-process-type or to concrete use cases. The studies of Bettacchi et al. and Nuritha/Er indicate that the inductive miner shows good performance when applying discovery techniques to certain use cases of a Make process [BPR16, NE19]. However, other algorithms may recognize additional properties of the processes that go beyond the pure workflow of the process model and that are of relevance as well, e.g., properties describing which different organizational units and which machine resources are involved in a manufacturing process. Further research is needed to validate these first assumptions, to provide more robust findings and to provide a selection framework for process mining algorithms. The more general framework to guide the selection and configuration of machine learning solutions in manufacturing proposed by Villanueva et al. may be a starting point for this research [VRM18]. Nevertheless, it has to be adapted to the specific needs of process mining.

Unstructured, cascaded, and non-linear processes

Since each application domain has its own characteristics, this also comes along with specific application problems that only occur in this domain [NE19]. However, there is little knowledge on resulting domain- and application-specific challenges. Only very few studies have addressed some manufacturing-specific challenges such as unstructured, cascaded, and non-linear manufacturing processes [BLP17, EAP15, EAW15, IB18, Ro19]. For instance, in case a product does not pass a test in a quality control gate, the processing order of this product does not follow the predefined order of the manufacturing process. The processes then become non-linear [Ch17, Wi20]. Here, the processing order typically includes loops from one step back to a preceding step, or even self-loops within a single manufacturing step. This means that data samples of a specific product occur multiple times in the related data set, but with different timestamps for one and the same process step. This makes it challenging to clearly associate the process instances identified by process mining with the real process steps and products. Although such unstructured, cascaded, and non-linear processes are typical for the manufacturing domain, no adequate solution exists to obtain the event log [EAP15, EAW15, Ro19] and to avoid “spaghetti-like” process models as a result [IB18, BLP17]. Thereby, it can be difficult to differentiate between expected and undesired process outcomes. Also, there is little knowledge how discovery techniques can deal with varying processes, i.e., where process steps may vary depending on the product variant being produced. The product variety that is inherent in manufacturing also increases the variety of underlying event data. It leads to complex data relations, to high data dimensionalities, and to a complicated interpretability of event data [Wi20, Wu16]. Hence, Intayoad/Becker mention that experts with domain knowledge have to be properly involved when planning an application project in manufacturing [IB18].

Integration and fusion of heterogenous data sources

Another main challenge for implementing process mining in manufacturing is a huge disconnect between physical flow of materials and the digital information flow. As complex, unstructured, and non-linear processes are often accompanied with heterogeneous data sources and IT systems, data quality and data integration of various data sources are of great importance in manufacturing [BLP17, NA17]. Here, a problem is the assumption of process mining that a process instance and its event data can be traced and clearly assigned through the entire process. In manufacturing, however, this can often only be the case over a limited segment of the process, e.g., over a single manufacturing line. A process change destroying the uniqueness of a process instance, can cause problems for process mining applications. This problem is even intensified by the unstructured, cascading, and non-linear nature of manufacturing process, as well as by the high variety of underlying products mentioned above.

Furthermore, the increasing use of sensor technology in the shop floor area provides new data sources for process analysis [AB20]. As a result of Industry 4.0 and the ongoing digitization, more and more sensors are being installed on machines and measuring stations [Gr16]. Hence, the generated data from those sensors are highly relevant for process mining in manufacturing as they contain additional and unique information. However, the integration of sensor data with machinery or ERP data sources is challenging, as sensor data are usually not linked to discrete process steps. In fact, no explicit or only incomplete key relationships (e.g., primary and foreign key relations) exist between both data sources. This makes the integration of such data sources difficult and can significantly increase the effort in terms of time and resources.

Hence, significant need for research exists especially for integrating and fusing heterogeneous data sources in process mining [BLP17, IB18, Na17]. This is underpinned by the fact that almost all studies apply process mining exclusively on ERP or MES data (except for [AB20]). So, they do not integrate data from various sources into one transformed event log. However, a combination of ERP, machinery and sensor data seems promising as this enables both an overall view on and a deep dive into end-to-end processes [Gr16]. Hence, existing process mining tools need to be enhanced with data integration features or be combined with other tools that deliver these features (e.g., Talend Open Studio for Data Integration).

Inter-organizational process mining

As manufacturing companies are interconnected in global supply chains, more and more of such inter-organizational processes are supported by IT systems. However, all identified studies analyze intra-organizational manufacturing processes and only use data from one company. Hence, the application of process mining for analysis of such inter-organizational processes should be in the scope of further studies [EA14]. However, this endeavor will most likely face a lot of problems. Not only heterogenous data sources within one company, but multiple and even more diverse data sources from other involved companies need to be integrated into consistent event logs. This will intensify already existing problems. Furthermore, it requires the involved parties to share confidential data. Nevertheless, this seems to be a promising way to optimize inter-organizational manufacturing processes, reducing the often-cited bullwhip effect in supply chains.

6 Conclusion

Process mining constitutes an important data-driven approach to gain a profound process knowledge and to pave the way for process optimizations. Process mining in manufacturing constitutes a novel and thus rather unexplored research field. Therefore, this paper provides an overview of various use cases for analyzing manufacturing-related processes. Our SCOR-based classification of the use cases gives an outline where process mining can be an alternative to existing tools. It especially helps practitioners identify suitable use cases for process mining, as the SCOR-model is implemented in many companies. Furthermore, we identify research gaps that need to be filled to ensure a broad adoption of process mining in the manufacturing domain. These research gaps are summarized in Table 2.

Tab. 2: Research agenda summarizing the identified research gaps for the application of process mining in manufacturing

Research Gap	Description
Consideration of process types and mining categories	Stronger focus on Deliver, Return and Enable process types, as well as on the mining categories conformance checking and process enhancement
Selection of algorithms for given use cases	Develop a selection framework which assigns algorithms to a process type or to concrete use cases
Handling of unstructured, cascaded, and non-linear processes	Develop adequate solutions to obtain event logs from such complex and dynamic processes and to prevent “spaghetti-like” process models
Integration and fusion of heterogenous data sources	Implement appropriate methods for data integration and fusion
Inter-organizational process mining	Examine and validate the use of process mining for inter-organizational process analysis

Here, we see addressing unstructured, cascaded, and non-linear processes as well as the integration and fusion of heterogenous data sources as most important. Those challenges are present in almost every manufacturing environment [Wi20] and are also linked to other gaps, e.g., to inter-organizational process mining. Also, the development of a use-case-related selection framework of algorithms seems valuable, especially for practitioners.

Bibliography

[AB20] Altan, Z.; Birgün, S.: Using Process Mining Approach for Machining Operations. In: (Durakbasa, N. M.; Gençyılmaz, M. G. Hrsg.): Proceedings of the International Symposium for Production Research, Springer, Cham, S. 452-464, 2020.

[BLP17] Becker, T.; Lütjen, M.; Porzel, R.: Process Maintenance of Heterogeneous Logistic Systems – A Process Mining Approach. In (Freitag, M.; Kotzab, H.; Pannek, J. Hrsg.): Dynamics in Logistics, Springer, Cham, S. 77–86, 2017.

[BPR16] Bettacchi, A.; Polzonetti, A.; Re, B.: Understanding Production Chain Business Process Using Process Mining: A Case Study in the Manufacturing Scenario. In (Krogstie, J.; Mouratidis, H.; Su, J. Hrsg.): Proc. 26th Int. Conf. on Advanced Information Systems Engineering CAiSE 2016, Springer, Cham, S. 193-203, 2016.

[Ch17] Cheng, Y. et al.: Data and Knowledge Mining with Big Data Towards Smart Production. Journal of Industrial Information Integration, 9/17, S. 1-13, 2017.

[Da18] Dakic, D. et al.: Business Process Mining Application: A Literature Review. In (Katalinic, B. Hrsg.): Proc. 29th Int. Symposium, DAAAM Int., S. 866-875, 2018.

[DSK17] Dišek, M.; Šperka, R.; Kolesár, J.: Conversion of Real Data from Production Process of Automotive Company for Process Mining Analysis. In (Jezic, G. et al. Hrsg.): Agents and Multi-Agent Systems Technologies and Applications, Springer, Cham, S. 223-233, 2017.

[EA14] Er, M.; Astuti, H. M.: A Case Study on Process Mining Implementation in Modeling Supply Chain Business Process – A Lesson Learnt. In (Pujawan, I. N.; Vanany, I.; Baihaqi, I. Hrsg.): Proc. 6th Int. Conf. on Operations and Supply Chain Management, Department of Industrial Engineering, Institut Teknologi Sepuluh Nopember (ITS), Indonesia, S.808-819, 2014.

[EAP15] Er, M.; Astuti, H. M.; Pramitasari, D.: Modeling and Analysis of Incoming Raw Materials Business Process: A Process Mining Approach. International Journal of Computer and Communication Engineering, 4/15, S. 196-203, 2015.

[EAW15] Er, M.; Astuti, H. M.; Wardhani, I. R. K.: Material Movement Analysis for Warehouse Business Process Improvement with Process Mining: A Case Study. In (Bae, J.; Suriadi, S.; Wen, L. Hrsg.): Asia Pacific Business Process Management, Springer, Cham, S.115-127, 2015.

[Er18] Er, M. et al.: Analysis of Production Planning in a Global Manufacturing Company with Process Mining. Journal of Enterprise Information Management, 31/18, S. 317-337, 2018.

[Ga19] Garcia, C. et al.: Process Mining Techniques and Applications – A Systematic Mapping Study. Expert Systems with Applications, 133/19, S. 260-295, 2019.

[Gr16] Gröger, C. et al.: A Mobile Dashboard for Analytics-based Information Provisioning on the Shop Floor. International Journal of Computer Integrated Manufacturing 29/16, S. 1335-1354, 2016.

[HSW04] Huan, S. H.; Sheoran, S. K.; Wang, G.: A Review and Analysis of Supply Chain Operations Reference (SCOR) Model. Supply Chain Management: An International Journal, 9/04, S. 23-29, 2004.

[IB18] Intayoad, W.; Becker, T.: Applying Process Mining in Manufacturing and Logistic for Large Transaction Data. In (Freitag, M.; Kotzab, H.; Pannek, J. Hrsg.): Dynamics in Logistics, Springer, Cham, S. 378-388, 2017.

[Ji18] Jimenez, J.-F. et al.: Using Process-mining for Understating the Emergence of Self-organizing Manufacturing Systems. IFAC-PapersOnLine 51/18, S. 1618-1623, 2018.

[KRP19] Knoll, D.; Reinhart, G.; Prüglmeier, M.: Enabling Value Stream Mapping for Internal Logistics Using Multidimensional Process Mining. Expert Systems with Applications 124/19, S. 130-142, 2019.

[Me17] Meincheim, A. et al.: Combining Process Mining with Trace Clustering: Manufacturing Shop Floor Process - An Applied Case. In (IEEE Hrsg.): Proc. of the 29th IEEE Int. Conf. on Tools with Artificial Intelligence, IEEE, S. 498–505, 2017.

[Mu06] Mula, J. et al.: Models for Production Planning Under Uncertainty: A review. International Journal of Production Economics, 103/06, S. 271-285, 2006.

[NWD19] Nagy, Z.; Werner-Stark, A.; Dulai, T.: Using Process Mining in Real-Time to Reduce the Number of Faulty Products. In (Welzer, T. et al. Hrsg.): Advances in Databases and Information Systems, Springer, Cham, S.89-104, 2019.

[Na17] Natschläger, C. et al.: A Practical Approach for Process Mining in Production Processes. In (Piazolo, F. et al. Hrsg.): Innovations in Enterprise Information Systems Management and Engineering, Springer, Cham, S. 87-95, 2017.

[NE19] Nuritha, I.; Er, M.: Behavioural Similarity Measurement of Business Process Model to Compare Process Discovery Algorithms Performance in Dealing with Noisy Event Log. In (Samsonovich, A. V.; Klimov, V. V. Hrsg.): Procedia Computer Science Pro. of the 5th Information Systems Int. Conf., S. 984–993, 2019.

[Pa15] Park, M. et al.: Workload and Delay Analysis in Manufacturing Process Using Process Mining. In: Bae, J., Suriadi, S., Wen, L. (Hg.): In (Bae, J.; Suriadi, S.; Wen, L. Hrsg.): Asia Pacific Business Process Management, Springer, Cham, S.138-151, 2015.

[Pa13] Paszkiewicz, Z.: Process Mining Techniques in Conformance Testing of Inventory Processes: An Industrial Application. In (Abramowicz, W. Hrsg.): Business Information Systems Workshops, Springer, Cham, S.302-313, 2013.

[Pi17] Pika, A. et al.: Analysing an Industrial Safety Process Through Process Mining: A Case Study. In (Mathew, L. et al. Hrsg.): Asset Intelligence through Integration, Springer, Cham, S. 491-500, 2017.

[RC17] Rbigui, H.; Cho, C.: Purchasing Process Analysis with Process Mining of a Heavy Manufacturing Industry. In (IEEE Hrsg.): Int. Conf. on Information and Communication Technology Convergence, IEEE, S. 495–498, 2017.

[RC09] R'bigui, H.; Cho, C.: Customer Oder Fulfillment Process Analysis with Process Mining. In (Association for Computing Machinery Hrsg.): Proc. of the 15th Int. Conf. on Mechatronics and Machine Vision in Practice, New York, S. 247–252, 2009.

[RAB18] Ribeiro, R.; Analide, C.; Belo, O.: Improving Productive Processes Using a Process Mining Approach. In (Rocha, A. et al. Hrag.): Trends and Advances in Information Systems and Technologies, Springer, Cham, S. 736-745, 2018.

[Ro19] Roldán, J. J. et al.: A Training System for Industry 4.0 Operators in Complex Assemblies Based on Virtual Reality and Process Mining. Robotics and Computer-Integrated Manufacturing, 59/19, S. 305-316, 2019.

[Ro09] Rozinat, A. et al.: Process Mining Applied to the Test Process of Wafer Scanners in ASML. IEEE Transactions on Systems, Man and Cybernetics, 39/09, S. 474-479, 2009.

[Ru18] Ruschel, E. et al.: Establishment of Maintenance Inspection Intervals: An Application of Process Mining Techniques in Manufacturing. Journal of Intelligent Manufacturing 467/18, S. 53-72 , 2018.

[TSS16] Thomé, A. M. T.; Scavarda, L. F.; Scavarda, A. J.: Conducting Systematic Literature Review in Operations Management. Production Planning & Control, 27/16, S. 408-420, 2016.

[TS16] Tu, T. B. H.; Song, M.: Analysis and Prediction Cost of Manufacturing Process Based on Process Mining. In (ICIMSA Hrsg): ICIMSA Int. Conf. on Industrial Engineering, Management Science and Applications, IEEE, S. 1-5, 2016.

[Va12a] van der Aalst, W. et al.: Process Mining Manifesto. In (Daniel, F.; Barkaoui, K.; Dustdar, S. Hrsg): Business Process Management Workshops, Springer, New York, S. 169-194, 2012.

[Va12b] van der Aalst, W.: Process Mining: Overview and Opportunities. ACM Transactions on Management Information Systems, 3/12, S. 1-17, 2012.

[Va16] van der Aalst, W.: Process Mining. Springer, Berlin, 2016.

[VRM18] Villanueva Zacarias, A.; Reimann, P.; Mitschang, B.: A Framework to Guide the Selection and Configuration of Machine-Learning-based Data Analytics Solutions in Manufacturing. In (Wang, L. Hrsg.): Proc. of the 51st CIRP Conference on Manufacturing Systems, Elsevier, S. 153-158, 2018.

[VW04] van der Aalst, W., Weijters, A.: Process mining: A Research Agenda. Computers in Industry, 53/04, S. 231-244, 2004.

[Wi20] Wilhelm, Y. et al.: Data Science Approaches to Quality Control in Manufacturing: A Review of Problems, Challenges and Architecture. In: Springer Proceedings Series Communications in Computer and Information Science (CCIS), 2020.

[Wu16] Wuest, T. et al.: Machine Learning in Manufacturing: Advantages, Challenges, and Applications. Production & Manufacturing Research, 4/16, S. 23-45, 2016.

[Zh11] Zhou, H. et al.: Supply Chain Integration and the SCOR Model. Journal of Business Logistics, 32/11, S. 332-344, 2011.