Process Mining in Manufacturing: Goals, Techniques and Applications

Darko Stefanovic, Dusanka Dakic, Branislav Stevanov, Teodora Lolic

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Darko Stefanovic[1[0000-0001-9200-5092]], Dusanka Dakic[2[0000-0002-1707-7616]], Branislav Stevanov[3[0000-0002-0211-2271]] and Teodora Lolic [4[0000-0001-5522-6558]]

[1,2,3,4] University of Novi Sad, Faculty of Technical Sciences, 21000 Novi Sad, Serbia
dakic.dusanka@uns.ac.rs

Abstract. Process mining is a discipline positioned between business process management and data mining. It applies algorithms on real event data extracted from information systems that support business processes, to construct as-is process models, and improve them automatically. The benefits can be versatile, from gaining insight into the real execution of a process, to detecting process bottlenecks, activity loops, or social networks of process resources. Several literature reviews have focused on the application of process mining in the healthcare industry and on process mining discipline in general, without the reviews of other application domains. This paper presents the results of a systematic literature review on case studies of process mining projects applied in the manufacturing industry. Case studies are analyzed according to the following aspects: project goals, information systems or devices/equipment that generate event data, particular business processes, event log characteristics, different types and perspectives of process mining performed, tools and techniques used for preprocessing activities, discovery, conformance checking, process enhancement, and social network analysis. Finally, an attempt is made to discover the impact of goals, types of processes, and event log characteristics on the selection of process mining types, perspectives, tools, and techniques.

Keywords: process mining, manufacturing, literature review.

1 Introduction

With the increasing availability and lower cost of technology, most manufacturing organizations can manage their business processes with some information system (Enterprise Resource Planning - ERP or Manufacturing Execution System - MES) [1, 2, 3]. Furthermore, in the Era of Industry 4.0 and big data [4], modern manufacturing systems generate a large amount of data that has the potential to become actionable information resources. Different data analysis techniques were used for the analysis of processes specific to the manufacturing industry, such as manufacturing and maintenance management processes [5]. Business intelligence, knowledge discovery, and data mining are some of the tools that fill the need for automated data analysis. Process mining is a new research field that enables the automatic discovery of business processes and numerous additional process enhancement techniques, such as performance analysis. It is defined by the IEEE Task Force on Process Mining, as follows [6]: "The idea of process mining is to discover, monitor, and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs readily available in today's (information) systems."

Process mining has been mostly applied in the healthcare industry, following with information technology, finance, and manufacturing industries [7]. Literature reviews of case studies in the healthcare industry [8], as well as several reviews of process mining applications [7] and state of the art [9], proved the feasibility and applicability of process mining. However, no study focuses on the applicability and benefits of process mining in the manufacturing industry. This paper aims to discover specific information found in case studies in the manufacturing industry through a systematic literature review that is assumed to be relevant for the future conduction of process mining projects in the manufacturing industry.

Firstly, it is relevant to discover which information systems, manufacturing devices/equipment, and business processes are analyzed in these case studies, as well as project goals. Event log characteristics can also be meaningful, as they can impact the decision on tools and techniques. Preprocessing activities, found to be the most difficult to perform, are also analyzed based on utilized tools and techniques. Furthermore, there are three types of process mining that will be observed: discovery, conformance, and enhancement [6]. Process discovery techniques produce a process model from an event log without using any a priori information about the process. Conformance compares the discovered process model with an event log of the same process and is used to check if event data conforms to the model. Enhancement improves an existing process model by using information about the actual process recorded in the event log. There are also different process mining perspectives [6]. The control-flow or process perspective focuses on the control-flow, i.e., the ordering of activities, and it is equivalent to discovery. The case and time perspectives are usually performed together [7], as they are comparable to process enhancement. The organizational perspective (social network analysis) focuses on information about originators in the log, i.e., which actors\performers are involved and how they are related. These different types and perspectives are used to solve particular problems that occur in real-life processes, and it is essential to outline their share in process mining applications. This paper will also describe different tools and techniques that were applied, grouped by types and perspectives of process mining. The results of this systematic literature review will tackle the benchmarking challenges of process mining and help process analysts in the manufacturing industry gain insight into the detailed possibilities and benefits of process mining applications.

The remainder of the paper is organized as follows. Section 2 describes the design of a systematic literature review. Section 3 presents the results of the review, and Section 4 concludes the paper and presents future work.

2 Research Design

A comprehensive and well-structured literature review firstly elaborates on the need for a systematic literature review, then formulates research questions, search strategy, study selection criteria, and performs study quality assessment [10]. Although there are papers that elaborate on the usefulness of process mining in the manufacturing industry, there are no literature reviews that offer summed information and conclusions on the topic, except [7], where authors reviewed process mining in all industries. The following research questions are established:

RQ1: What are the main goals of process mining projects in manufacturing?

RQ2: Which information systems, devices, or equipment are the generators of the event data, and which company processes are being automated?

RQ3: What are the characteristics of analyzed event logs?

RQ4: What preprocessing tools and techniques were used?

RQ5: What types and perspectives were performed, and which tools and techniques were used?

RQ6: Do goals, types of processes, or event log characteristics influence the selection of process mining types, perspectives, tools, and techniques?

The SCOPUS database and Google Scholar were searched with the following search terms: “Process mining” and “manufacturing” and “case studies”. The search resulted in 256 papers.

Inclusion criteria applied to papers are:

IC1: Papers have to be published full-text as articles or conference proceedings.

IC2: Paper has to present a case study.

IC3: The paper has to be written in English.

Exclusion criteria applied to papers are:

EC1: Paper presents a case study from other industries.

EC2: Paper presents the same case study, written as a different publication.

EC3: Paper is referencing process mining but is using other technologies in the case study.

After applying defined inclusion and exclusion criteria on available papers, papers were critically appraised based on their relevancy and type of information they contained. Finally, there were 14 primary studies available for data extraction.

Flow diagram of the systematic literature review process is presented in Fig. 1.

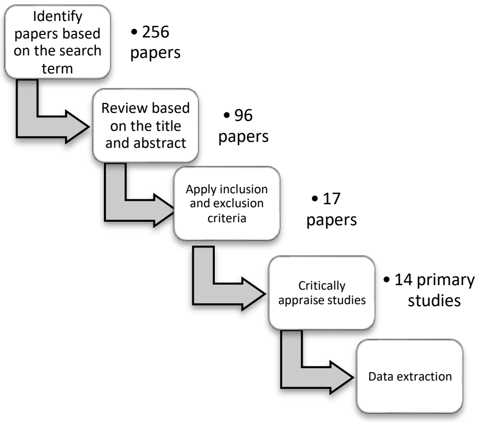

Fig. 1. Systematic literature review flow diagram

3 Data Extraction Results

Besides the process discovery, process mining was successfully applied to detect throughput and waiting times of a process and to discover bottlenecks and feedback loops [12, 14, 15, 16, 18, 20, 21, 23, 24]. Moreover, process mining SNA techniques were used for finding the roles and relationships of the resources (e.g., machines, employees) [12, 15, 18, 20, 22], presented through resource networks. Other applications of process mining were focused on detecting compliance issues with the expected behavior of a process [11, 12, 13, 16], predicting manufacturing cost based on production volume and time [17], estimating process cycle times [19], and discovering business essential process variants before undergoing an ERP implementation project [23]. Fig. 2 presents the types of publications by year.

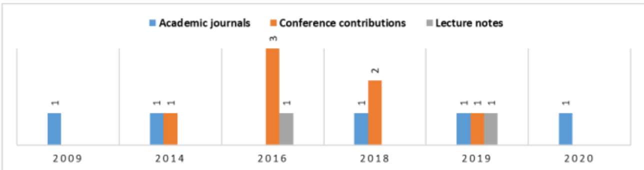

Fig. 2. Types of publications by year

Fig. 3. presents the goals of the process mining projects, sorted descendingly by the number of case studies with the same goal.

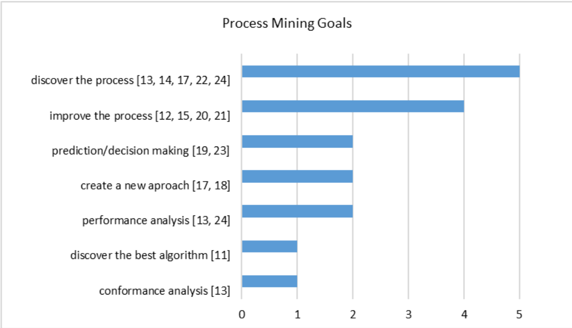

Fig. 3. Number of papers with the same process mining goal

Fig. 4. presents processes from the manufacturing industry that were the subject of process mining. The manufacturing process [16, 17, 18] and the procurement process [13, 21, 23] were analyzed the most, following with the production planning [15, 20], incident management [12, 24], maintenance management [22, 25], product assembling [11] and product testing process [17]. Mostly used information system was the ERP system [13, 15, 20, 23], which supported all procurement and production planning processes. Other processes were supported by the Supply Chain Management system [11], the MES [17], the Shipbuilding Processing Plan Management system [21], Supervisory Control And Data Acquisition (SCADA) system [24], and a problem handling system [12]. As manufacturing devices and equipment that can generate event data are considered, CNC machine [19], programmable logic controller, and robot stations [22] were analyzed.

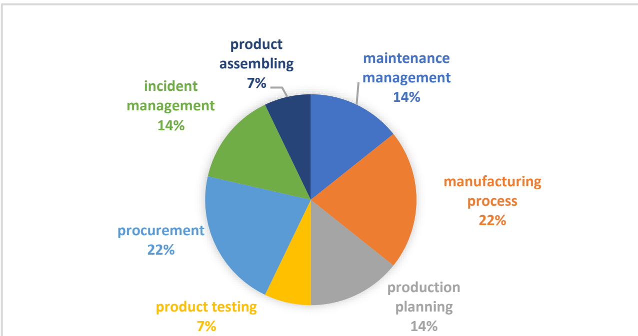

Fig. 4. Analyzed processes in the manufacturing industry

Table 1. presents information about performed techniques, algorithms, and tools in all case studies grouped by different process mining types and perspectives. It can be concluded that all case studies performed process discovery and control-flow perspective. Enhancement was performed in 57% of the case studies [13, 14, 15, 16, 17, 18, 20, 24]. Conformance checking was performed in 28% of the case studies [13, 14, 15, 16] and SNA in 21% [16, 18, 20].

Table 1. Algorithms/techniques and tools

		Tools					
	Techniques/algorithms	ProM	Disco	ProM Import	Manual	KeyPro	New tool
Preprocessing	Attribute filtering		20, 21		12		
	Filter out artificial start and end act.		13, 19, 20				
	Filter out incomplete cases		13, 20, 21				
	Filter out infrequent cases		13				
	Convert to MXML, inversion filter	14		14			
	Add attributes to event log				17	23	
Discovery (control-flow)	Heuristic miner	11,13, 14, 15, 16, 18					12
	Fuzzy miner		19, 20, 21, 24				
	Inductive miner	11, 13, 22					
	ILP miner, Evolutionary tree miner, alpha algorithm	11					
Enhancement (case/time)	Bottleneck analysis	14, 17	20, 22, 24				12
	Calculate throughput time	16, 18	20, 21				
	Detect feedback loops		15, 20, 21, 23				
	Performance analysis plug-in	11, 16					
	Dotted chart analysis	18, 20					
	Process variant analysis		15				
	LTL checker	16					
	Pattern abstraction visualizer	20					
	Process model-enhanced cost plug-in						17
Conform.	Conformance checking plug-in	11, 16					
	Rule-based conformance checking				13		
	Manual conformance checking				12		
Social network	Social network analysis plug-in	16, 18, 20					
	Originator impact and role analysis						12
	Inductive miner	22					

To answer the RQ6, firstly, it was analyzed if the case studies with the same goal had performed the same process mining types and perspectives. It was concluded that there are patterns by which process mining was conducted based on the overall goal of the case study. Case studies that aimed to discover the process performed control-flow perspective (discovery type) in 100% of the cases and case/time perspective (enhancement) in 80%. The case studies with the goal to perform performance analysis used control-flow and case/time perspectives. The case study with the goal of performing conformance analysis conducted all three types of process mining. Case studies that aimed to develop a new approach for process mining in manufacturing performed discovery and enhancement. The case studies with the goal to improve the process conducted process discovery in 100%, process enhancement in 50%, conformance checking in 25%, and organizational mining in 25% of the cases. The case studies with the goal to predict the process flow or use process mining for decision making, performed only process discovery. Finally, case studies that aimed to discover the best algorithm for process mining in manufacturing performed only process discovery. Secondly, it was analyzed if a process type influences the process mining types and perspectives. Because most process types were discovered and enhanced, there was no significant correlation. However, all production planning processes and 60% of procurement processes were supported by an ERP system. It was discovered that event log characteristics such as event log format, size, and number of cases and activities do not influence types and perspectives of process mining nor chosen tools and techniques.

4 Conclusion

This paper aimed to gain insightful information about the application of process mining in the manufacturing industry. The data extracted from the case studies show an overview of the goals of process mining projects, information systems, analyzed processes, and event log characteristics. More significant is an overview of all techniques, algorithms, and tools, grouped by the process mining types and perspectives. Finally, the paper presented an analysis of the impact that goals, processes, and event log characteristics had on the selection of process mining types, perspectives, and techniques/algorithms. The discovered relationships between the key features of process mining could be tested as hypotheses, by including a higher number of case studies, even considering all industries in which process mining is applied.

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