Politecnico di Torino

Master’s Degree Final Year Project

Academic Year 2023/2024

THE USE OF PROCESS MINING TECHNIQUES IN MANUFACTIRING SYSTEMS

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Introduction

In today's industrial settings, achieving operational excellence and continual improvement is critical to maintaining a competitive advantage. To do this, firms are increasingly turning to data-driven approaches like Process Mining (PM), which provides strong insights into the complexities of operational processes. The use of PM holds promises for increasing efficiency and effectiveness, particularly in the manufacturing sector, where complex interrelated processes are prevalent (Birk et al., 2021).

In comparison to other fields such as healthcare, the use of PM in manufacturing is largely unknown. Existing research reveals a scarcity of studies focusing on the study of manufacturing processes using PM, with less emphasis placed on the integration of diverse data sources (Birk et al., 2021). This gap highlights the need for more research into how PM may be effectively applied to multi-level interrelated manufacturing processes with complex process structures and different data sources.

Drawing on insights from several key articles, this thesis examines and discusses a number of research articles on process mining in manufacturing systems. The paper employs a comparative approach to address the barriers preventing the adoption of process mining in the manufacturing sector, and to suggest solutions for improving transparency and optimizing processes within these complex systems.

Process Mining

Definition of process mining

Process mining, as defined by Brock et al. (2023), is at the vanguard of modern manufacturing analytics, providing essential insights into business processes through the methodical analysis of event data collected from multiple IT systems. With its deep in the manufacturing sector's pursuit of operational excellence, process mining has evolved as a critical instrument for increasing efficiency and driving cost-cutting initiatives.

How does process mining work?

The method by which process mining reconstructs and visualizes the real process flows, deviations, and bottlenecks within an organization's operations is by analyzing event data that is gathered during the execution of business processes. Process mining often entails three primary processes, according to Rudnitckaia et al. (2022): discovery, compliance testing, and enhancement.

Focuses of Process mining

Process mining considers several views, including control flow, organizational, case, and timestamps. While much of the work on process mining focuses on the sequence of operations (i.e., control), the other views are also useful for management teams Rudnitckaia et al. (2022). Organizational viewpoints can reveal the various resources inside a process, such as particular job positions or departments, whereas time perspectives can highlight bottlenecks by monitoring the processing time of distinct events within a process.

Process mining applications in manufacturing

Manufacturing organizations, motivated by imperatives such as globalization and personalization, are increasingly resorting to process mining to optimize operations and react to changing market needs. This rising reliance on process mining is supported by the widespread use of digital technology in manufacturing, which has resulted in the development and collection of massive amounts of data from enterprise systems such as Enterprise Resource Planning (ERP) and Product Lifecycle Management (PLM). However, as Brock et al. (2023) note, the route from data collection to actionable insights is riddled with difficulties, with up to 80% of project effort frequently allocated to processes such as data extraction and transformation.

Despite these obstacles, the benefits of process mining are apparent, providing manufacturers with transparency into their existing processes, the opportunity to monitor process performance, and significant insights for process optimization. Furthermore, the interdisciplinary nature of process mining initiatives involves collaboration across multiple departments, including as IT and sales, emphasizing the importance of cross-functional teamwork in successful process mining endeavors (Brock et al., 2023).

Innovative Approaches to Enhance Industrial Manufacturing Processes

The integration of process mining and value stream approaches is a crucial strategy for improving data-driven decision-making in industrial production processes. According to Rudnitckaia et al. (2022), it's critical to use advanced analytics tools to maximize the value of production system and process data. By doing so, businesses may optimize their current business processes and boost productivity and effectiveness throughout the board. This is consistent with the main thesis put forth by Mayr et al. (2022), who emphasize the necessity of quick decision-making in response to rapidly shifting market demands by highlighting the growing use of sensors and sophisticated sensor data in the context of Industry 4.0. The importance of applying data-driven strategies to improve industrial processes and deal with the difficulties presented by changing market conditions is emphasized in both publications.

In industrial manufacturing processes, time becomes a crucial factor that affects both optimization and service levels (Rudnitckaia et al., 2022). Manufacturing organizations can make proactive decisions by gaining early knowledge of delays in production time, cycle time, and process behavior by highlighting the significance of time and its accuracy in the information system. This focus on timing is consistent with the concept put forth by Mayr et al. (2022), which uses digital twins to monitor and optimize production processes in real-time. In manufacturing ecosystems, both pieces acknowledge the critical role that time plays in directing decision-making procedures and risk-reduction tactics. Though they approach it in different ways, the integration of value stream techniques and process mining, as supported by Rudnitckaia et al. (2022), and the methodology put forth by Mayr et al. (2022), both aim to improve process optimization and risk mitigation strategies in industrial manufacturing.

Figure 1 illustrates the three stages of the suggested process: mapping, analyzing, and improving.

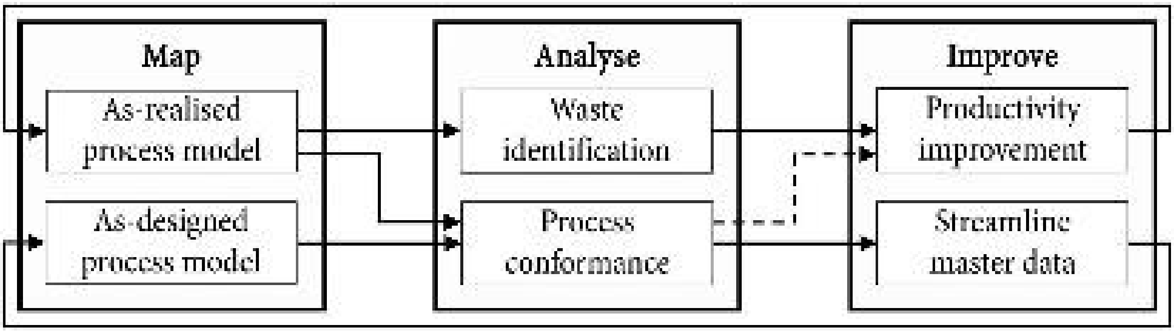

Figure 1 Process mining procedure for productivity improvement in manufacturing (Lorenz et al., 2021)

Events and event logs are critical components of process mining. An event log is a record of business events that occur inside an organization that captures the sequence of operations in operational processes. According to Hejazi et al. (2023), event logs include essential information on an organization's performance while carrying out its business processes, providing insights into process behavior and performance. These logs are based on actual occurrences and activities within the firm, rather than preconceived plans or designs for business operations.

Event logs constitute the basis for process mining, which is evaluating event data to extract important information about process behavior, performance, and adherence to predefined standards.

Below is an example of a Web Server data that may be used for process mining:

SessionID	Page	Timestamp	CookieID	DataCenter	SiteVersion
487434	portal.aspx	2016-01-01 15:34:01	A	phoenix	1.12
487434	dashboard.aspx	2016-01-01 15:34:15	A	phoenix	1.12
487434	purchaseorderreport.aspx	2016-01-01 15:34:30	A	phoenix	1.12
487435	portal.aspx	2016-01-01 14:01:10	B	phoenix	2
487435	help.aspx	2016-01-01 14:03:23	B	phoenix	2
487435	contactus.aspx	2016-01-01 14:04:07	B	phoenix	2
487436	portal.aspx	2016-01-01 17:11:17	A	phoenix	1.12
487436	myteam.aspx	2016-01-01 17:12:41	A	phoenix	1.12
487436	expensereports.aspx	2016-01-01 17:12:55	A	phoenix	1.12

Figure 2 Event Log Process Mining

This figure shows us the most important process mining approaches, such as discovery, compliance testing, and enhancement.

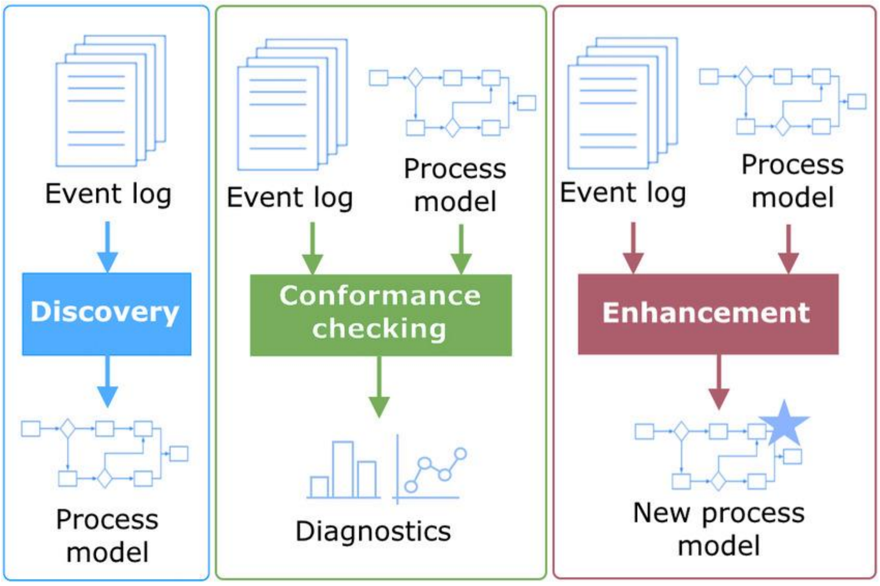

Figure 3 Process Mining Techniques (Batista, Edgar. 2022)

Discovery

Discovery is a fundamental process mining technique that includes constructing process models from event log data to characterize the observed behavior of a system. Several algorithms for process discovery have been created, including the alpha miner, heuristic miner, inductive miner, and fuzzy miner (Lorenz et al., 2021). These algorithms seek to create a process model that best matches the observed behavior recorded in the event logs.

Conformance Checking

Conformance checking is another key process mining technique that determines how well observed process behavior matches a preset process model (Lorenz et al., 2021). It seeks to uncover discrepancies and deviations between observed behavior in event logs and expected behavior as stated by the process model.

Enhancement

Enhancement strategies in process mining rely on insights gained from process discovery and compliance testing to optimize and improve processes (Lorenz et al., 2021). These strategies use the observed bottlenecks, deviations, and inefficiencies to carry out targeted interventions and enhancements that improve process performance.

Process mining approaches provide a robust collection of tools for analyzing, optimizing, and enhancing processes across multiple domains. From process discovery to conformance testing and enhancement, these strategies give vital insights that help firms improve efficiency, cut costs, and achieve better results. Using event log data and process models, firms may acquire a better knowledge of their operations and efficiently drive continuous improvement programs.

Event Logs for Process Mining in Manufacturing

With an emphasis on the use of event logs, Birk et al. (2021) and Friederich et al. (2022) offer insightful analyses of the use of Process Mining (PM) in the industrial sector. The foundation of process mining is comprised of event logs, which record the complex series of actions and occurrences in manufacturing settings. The significance of event logs in attaining process transparency and data-driven decision-making, they emphasize how event logs must incorporate data from several sources, including supervisory control and data acquisition (SCADA) and enterprise resource planning (ERP) systems, in order to provide a thorough understanding of manufacturing operations. Event logs are a rich source of data for PM analysis since they precisely preserve specifics like timestamps, physical part identification, and particular activity details (Birk et al., 2021).

In line with this, Friederich et al.'s (2022) research on smart manufacturing systems highlights the crucial function of event logs. They go into detail on how event logs make it easier to derive material flow and machine behavior models, which makes it possible to comprehend intricate industrial processes on a deeper level.

Event logs provide the foundation for thorough process analysis because they record crucial information including precise activity descriptions, identifiers for physical components or parts, and timestamps for timing activities.

The importance of event logs is emphasized by Friederich et al. (2022). In collaborative mining approaches, data from diverse sources is combined into event logs to create comprehensive models that span a range of system behaviors and features. It goes to show how event logs are vital for promoting increases in productivity and efficiency in manufacturing processes through their careful examination and use. (Friederich et al., 2022)

Both studies emphasize the critical role that event logs play in giving insights for process improvement and decision-making, making them essential tools for PM analysis in manufacturing.

Approaches to Process Monitoring and Optimization in Industrial Manufacturing

Process mining and value stream analysis in the context of industrial manufacturing depend heavily on techniques for conformance checking, discovery, and change detection as well as bottleneck detection techniques. Utilizing production system and process data for data-driven optimization and decision-making is made possible in large part by these techniques. While discovery techniques draw conclusions from event data to create thorough process models, conformance testing assesses conformity with expected models to find inefficiencies (Rudnitckaia et al., 2022). On the other hand, Mayr et al. (2022) draw attention to the shortcomings of conventional process monitoring in the context of Industry 4.0 and suggest combining Process Mining with Digital Twins to overcome them. By abstracting event logs from continuous process-state data, this method makes change detection and conformity verification possible in real-time. Furthermore, compared to the traditional reliance on discrete event logs, integrating continuous process-state data into event logs improves comprehension and enables prompt intervention (Mayr et al., 2022). Although they employ distinct tactics, both approaches seek to increase manufacturing's efficiency and competitiveness. Rudnitckaia et al. prioritize adherence to predetermined standards, whereas Mayr et al. place more emphasis on real-time monitoring and adaptation to changing operational requirements.

Digital Twins Alignment vs. Process Mining Integration

The methods of integrating process mining techniques and continuously aligning digital twins with actual production systems provide unique approaches in the quest to increase manufacturing efficiency. Chià et al. (2021) emphasize that in order to properly support decision-making processes, synchronization between digital twins and physical systems must be maintained. Their approach is to ensure that digital twins accurately reflect dynamic manufacturing processes by updating them quickly in response to changes in production systems.

Figure 4 shows the combination of digital twins and process mining in the form of process digital twins.

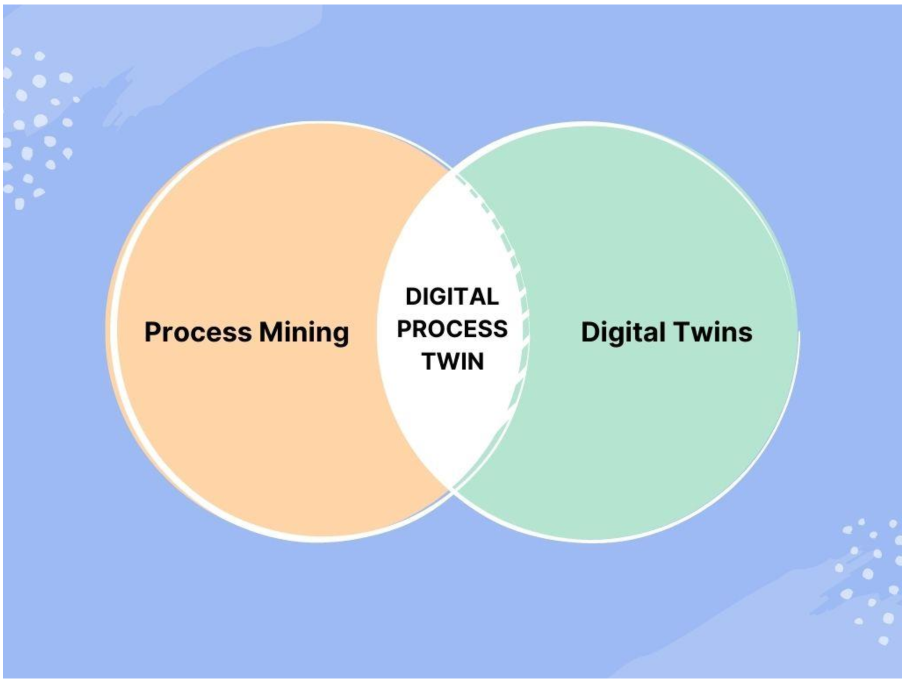

Figure 4 Digital process twins combine process mining methods and digital twins (Numminen, 2023)

On the other hand, Lorenz et al. (2021) overcome the shortcomings of conventional techniques like value stream mapping by putting forth a thorough three-phase strategy for incorporating process mining into make-to-stock manufacturing. They provide practical insights for improving production efficiency by showcasing the effectiveness of process mining in real-time productivity constraint identification and resolution through empirical validation. Although the goal of both strategies is efficiency optimization, Chiò et al. place more emphasis on real-time alignment between digital twins and physical systems, whereas Lorenz et al. prioritize process mining's dynamic study of actual process flows.

Data-Driven Techniques in Internal Logistics Systems

The utilization of data-driven techniques, such as process mining (PM) and discrete-event simulation (DES), in the context of internal logistics systems (ILS) has proven to be crucial in augmenting efficacy and curbing operating expenses. Although there are issues with data quality, PM provides insights into process data and reveals inefficiencies within ILS. By producing process data, resolving problems with data quality, and offering extensive datasets for analysis, DES enhances PM. Conversely, finding and analyzing workarounds in organizational processes is a major difficulty, especially in small and medium-sized organizations (Wijnhoven et al., 2023).

Particularly for SMEs, process mining shows promise as a means of identifying formal process irregularities. Furthermore, understanding the causes and implications of workarounds requires classifying them into several kinds (Wijnhoven et al., 2023). Both techniques use data-driven strategies, but they are different in terms of context and breadth. While process mining is largely concerned with identifying deviations from formal processes, particularly within SMEs, PM and DES concentrate on improving efficiency and cutting costs inside ILS by optimizing processes and addressing data quality concerns. This demonstrates the necessity of adopting customized methods for data-driven analysis based on the goals and organizational environment.

Integration of Process Mining into Life Cycle Assessment

The incorporation of Process Mining (PM) into Life Cycle Assessment (LCA) approaches is a viable approach to tackling the challenges that industrial organizations confront when assessing the environmental implications of their products and processes.

Challenges in Traditional LCA Methodologies

Traditional LCA methodologies, while extensively utilized, have drawbacks such as time-consuming analysis and static evaluation of specific goods (Ortmeier et al., 2021). The comprehensive examination of environmental implications across a product's life cycle requires significant time and resources, which frequently impedes continuous and dynamic study. Furthermore, the static nature of classic LCA approaches limits their capacity to capture the dynamic intricacies of modern industrial processes and product life cycles.

Benefits of Integration

By incorporating PM into LCA methodology, businesses can overcome the time limits and static nature of traditional LCA approaches while getting deeper insights into the environmental consequences of their goods and processes. This integration enables a more dynamic and continuous examination of environmental impacts, allowing businesses to adjust their processes in real time to fulfill sustainability objectives and legal requirements.

Conclusion

The study of Process Mining (PM) in modern manufacturing has proven its ability to transform operational excellence and drive continuous improvement. Throughout this thesis, we have looked at the definition of process mining, its applications in manufacturing, several process mining approaches, and its dynamic approach to change detection and adaptation. Furthermore, we investigated the integration of process mining into life cycle assessment (LCA) approaches.

Process mining emerges as an effective tool for manufacturing companies looking to optimize operations, respond to changing market demands, and traverse the intricacies of global production networks. Firms that use event log data and process models can obtain useful insights into their processes, uncover bottlenecks, and enhance resource usage throughout their manufacturing operations.

As we move forward in the digital age, the importance of process mining in manufacturing will expand. Its capacity to give real-time insights, optimize processes, and promote operational excellence makes it an essential tool for businesses looking to maintain a competitive advantage in today's changing industry. Manufacturing businesses can open up new avenues for innovation, efficiency, and long-term success by adopting and integrating process mining approaches.

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