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# FROM BPM TO PROCESS MINING: PRODUCTION PLANNING KPI ANALYSIS

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***Abstract***

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# FROM BPM TO PROCESS MINING: PRODUCTION PLANNING KPI ANALYSIS

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**Abstract**
*Production planning processes are often prone to long waiting times, redundant activities, and inconsistent production rates. Previous research explored the potential of integrating Business Process Management (BPM) with Process Mining (PM) to achieve production planning automation and digitization. This paper extends previous research by evaluating PM tools to analyze production planning Key Performance Indicators (KPIs). Research results include a discovered process map, identification of bottlenecks and key activities, and KPI analysis. The final contribution of this work is related to the potential application of such a solution for performance measurement, product improvement, and overall business enhancement.*

**Keywords**
*Business Process Management (BPM); Process Mining (PM); Business Process Automation (BPA); Key Performance Indicators (KPIs); Production Planning Business Process.*

## I. Introduction

Modern production requires constant improvements and maximum utilization of the latest information and communication technology (ICT). Nowadays, when technology is applied and implemented in all aspects of human life, the manufacturing industry is one of the main areas where ICT could have a great impact [1]. Minimal technological advancements can result in significant improvements in product development and quality. For such reasons, it is important to ensure continuous monitoring, maintenance, and optimization of manufacturing operations, including the production planning process.

Process mining (PM) represents a set of techniques for conducting process-centric analysis, with the power of automated process discovery, conformance checking, and model enhancement [2]. The essential part of process mining is an event log, i.e., a record of process instances. Apart from cases and process activities, an event log can store additional information about events, such as resource data, time elements, and other relevant attributes [2].

While process discovery creates a process model from the event log, conformance checking detects differences between the initial process model and the event log. The model enhancement also uses the event log to correct, expand, or complete the initial process model [2]. Process mining can be used for organizational analysis as well, apart from process model generation. This can provide valuable information about relationships between the company's resources – workers or machines. Additionally, process mining can visualize process attributes, such as production rate and product quantity, and detect potential problems related to process performance [3].

A comprehensive analysis of production processes, including frequency, performance, and social network analysis, can be performed using the process mining methodology. Therefore, process mining is recognized as a way to fully understand production planning processes and identify process inefficiencies. Subsequently, this paper aims to contribute to more efficient production planning by testing the potential of applying process mining and process management techniques in the context of process analysis and optimization.

The authors' first research concerning production planning automation in a mid-sized manufacturing company in Serbia focused on Business Process Automation (BPA) using Business Process Management (BPM) tools, such as Bonita [4]. The final contribution of this paper was a desktop application for semi-automated production planning business process support. The continuation of research evaluated integrating process mining with BPM and presented a conceptual solution for automating production planning processes using a process mining tool, Disco [5]. Specifically, the second research compared the AS-IS process model [5] with the TO-BE process model [4] to detect differences between the actual and desired process behaviour.

The current paper builds on previous research by examining how process mining and BPM enable production planning Key Performance Indicators (KPIs) analysis, apart from process automation. The study was performed on a synthetically generated event log using a simulated dataset related to production planning processes in the mentioned Serbian manufacturing company. The final contribution of this work represents the extension of previous research by adding KPI analysis through process mining. The generated event log contains performance metrics that were used to conduct frequency, performance, social network, and KPI analysis. In this way, the paper tested the potential of PM and BPM methodologies when used for production planning optimization.

The remainder of this paper is structured as follows. The following section introduces the process mining approach, along with a description of the process mining tools that were used during this research. The third section provides the methodology for researching production planning processes using process mining tools – Disco and ProM. The fourth section presents the research results, i.e., the results of frequency, performance, and social network mining. Additionally, this section presents calculated process and equipment KPIs, such as allocation and quality ratio. Section 4 also describes the recommendations for process enhancement, digitization, and modernization based on research results. Finally, section 5 discusses the key advantages of implementing the PM approach in the manufacturing industry, together with the conclusion of work, limitations of this study, and proposals for future research.

## II. Process Mining

In terms of the manufacturing industry, a digital model represents a software representation of a physical system, including all relevant characteristics and dynamics of the system [6]. Simulating such a model enables the analysis of complex systems, along with system configuration and resource allocation [6]. However, these simulations must ensure the model's reliability, i.e., the physical system and its digital model must be aligned. Additionally, data used for model generation must accurately represent the physical system. Lastly, the physical system must maintain the characteristics and rates that were used during model development [6].

At the beginning of the 21st century, process mining was introduced as a new method for data analysis [7]. The combination of techniques related to process mining facilitated digital model discovery, enabled comparison of actual and desired system behaviour, and led to the detection of unexpected issues and process deviations [6].

The digital model is usually presented in the form of a Petri net or some other process notation, such as BPMN or UML diagrams [8]. Such notation is used for mining all possible paths related to the process flow. Apart from the process perspective, process mining covers the organizational perspective regarding the actors who performed the activities, the case perspective that analyzes the process as a whole, and finally, the time perspective that examines the time and frequency of process events [8].

Several process mining algorithms were developed for model discovery support, classified into three main groups: deterministic algorithms, heuristic algorithms, and genetic algorithms. All of the mentioned algorithms provide a process model based on the event log registered by Process-Aware Information Systems (PAIS) [9]. In addition to process mining algorithms, numerous process mining tools were also introduced since the process mining discipline was first presented, including Disco, myInvenio, ProM, ProM Lite, SNP, etc [8]. These authors used Disco and ProM toolkits to conduct process mining, whose brief introduction is given in the following text.

Disco offers a simple and intuitive framework for visualizing, filtering, and managing event logs. This tool is particularly useful for performing frequency and performance mining due to its high capability for data preprocessing and generating process maps [8]. Disco can also generate a video of the business process's execution, which can be used to identify process bottlenecks [10].

On the other hand, ProM is an open-source tool that enables generating and exploring the business process model using countless available plug-ins. For such reasons, ProM represents one of the most dominant tools for conducting process mining analysis. Research showed that when discussing the IT industry, ProM is especially useful for organizational perspective analyses and conformance checking [8]. However, the difference between Disco and ProM refers to their supported discovery algorithms. While Disco uses the Disco (fuzzy) miner exclusively, ProM supports a variety of discovery algorithms, such as heuristic miner, genetic miner, $\alpha$-algorithm, etc. Nevertheless, this does not prevent the simultaneous use of both tools [11]. By exporting the event log into XES format in Disco, researchers can import the mentioned XES file into ProM. This enables users to use both Disco and ProM and gain maximum benefits [12].

This paper explores the potential of applying process mining for production planning enhancement, including the KPI analysis. Key performance indicators express quantifiable measurements of the company's critical success factors [13]. These indicators help organizations monitor crucial business processes, including production planning processes. By doing so, organizations can identify potential problems and implement necessary changes to improve production rates and customer satisfaction [13].

The international standard ISO 22400 defines a set of KPIs for performance evaluation in the manufacturing industry. Authors Zhu et al. [13] made further adjustments to the ISO 22400 standard's list of KPIs, intending to make them more suitable for the modern process industry. The mentioned researchers proposed a new KPI framework, i.e., the redefined KPIs, divided into two main groups – equipment performance indicators and process performance indicators [13]. Equipment KPIs are allocation ratio, utilization efficiency, and equipment load ratio [13]. On the other side, process KPIs include throughput rate, technical efficiency, quality ratio, actual to planned ratio, scrap ratio, finished goods ratio, and energy consumption [13].

Process mining software, such as Disco and ProM, enabled the KPIs analysis [14] and production planning enhancement. This can lead to reduced costs, improved product quality, and the accomplishment of strategic goals. The methodology for conducting KPI analysis using modern process mining tools is given in the following section of this paper.

## III. Methodology

The aim of applying process mining techniques was to discover and examine the production planning process map, with the additional objective of performing a KPI analysis.

The previous part of the research on the topic of automating production planning processes delivered the first version of the synthetic event log in CSV format [5]. The mentioned event log included the following columns: *CaseID, Activity, Resource,* and *Timestamp*. However, to perform a KPI analysis, the event log must contain relevant information related to different performance indicators, such as production rates, energy consumption, input material quantities, time elements, etc. For that reason, the event log used in earlier research [5] was modified and extended so that such metrics are included in the KPI analysis. Some of the metrics added to the event log and used for KPI calculation are:

1. Actual Production Rate: The achieved production output per unit time.
2. Maximum Production Rate: The theoretical maximum production output per unit time.
3. Planned Production Rate: The expected production output per unit time.
4. Actual Produced Quantity: The number of produced units.
5. Desired Product Quantity: The expected number of units to be produced.
6. Actual Faulty Product: The number of produced faulty products.
7. Planned Faulty Products: The expected number of faulty products to be produced.
8. Input Material Quantity: The amount of raw material used during production.
9. Energy Consumption: The energy used during production.
10. Planned Operation Time (POT): The scheduled time during which the equipment or process can be utilized.
11. Actual Busy Time (ABT): The actual time needed for process execution.
12. Actual Production Time (APT): The time needed for completing production activities, such as product scraping and assembling.
13. Actual Down Time (ADT): The time during which the equipment or process is delayed due to malfunctions, unavailability of resources, human errors, or other unplanned events.

Additionally, POT, ABT, APT, and ADT are correlated in the following way [13]:

$$ABT = APT + ADT \tag{1}$$

While the start and end timestamp columns represent when each activity started and finished performing, the added time elements are directly affected by the timestamp values. ABT represents the difference between the first and last timestamp in a case, thus summing the time spent on productive and non-productive activities. On the other hand, APT calculates the sum of executing productive activities only, such as product scraping and assembling. ADT is calculated as the difference between ABT and APT, reflecting different types of delays. Finally, POT has a value within ±30% of the ABT, illustrating the desired time for process completion. Furthermore, to bring the event log closer to real industrial production planning processes, stochastic waiting times between activities were also added.

After expanding the event log by the mentioned metrics, the values of each performance indicator were calculated based on the formulas given by Zhu et al. [13]. Then, the KPI values were divided into four categories: *low, medium, high*, or *extremely high*, completing the event log preparation.

The methodology for performing the process mining and KPI analysis of production planning processes is presented in the following:

1. Importing the event log into Disco: The synthetically generated event log, created using the Python programming language, was imported into Disco as a CSV file.
2. Data preprocessing: Event log filtering using Disco was used to clean the dataset and prepare it for process analysis.
3. Process map discovery: The event log was imported into Disco, and a process map was generated.
4. Frequency and performance analysis: Frequency and performance perspectives of the production planning process were analyzed to detect bottlenecks, long waiting times, and other process inefficiencies.
5. Production planning KPI analysis: In addition to frequency and performance analysis, Disco was used to examine KPIs, including allocation ratio, utilization efficiency, throughput rate, technical efficiency, quality ratio, and scrap ratio.
6. Event log conversion into XES standard format: By converting the event log into an XES file, data is prepared and ready for process mining using ProM.
7. Social network analysis: Since Disco does not support the generation of social networks [11], ProM is used for further organizational review.

As mentioned earlier, the benefits of implementing this solution include process model visualization, identification of the most frequently repeated process activities and their associated bottlenecks, and social network mining [15][16]. Relevant KPIs were also calculated and presented in this work. Following the research results, differences between the actual and desired process behaviour can be reduced to a minimum.

## IV. Research Results

The following text presents the findings related to data preprocessing, frequency, performance and social network mining, and finally, KPI calculation. After importing the event log into Disco, data preprocessing was performed, which included applying the *endpoint* filter to determine the number of orders ending with product storage. Disco showed that 9015 out of 10000 can be declared as completed, i.e., 90% of cases result in final goods being stored. These 9015 cases were then subject to further process analysis.

### *A. Frequency perspective*

Fig. 1 illustrates a fuzzy model of the production planning process generated in Disco. The absolute frequency and mean duration of an activity are given inside rectangles. The numbers next to the lines show the absolute frequency and mean duration of the path connecting two activities. Thicker lines relate to more frequent paths.

Analyzing the production planning frequency perspective given in Fig. 1, it can be concluded that the most frequent activities are Choosing Production Technology, Material Requisition, Production Operation, Product Scraping, Assembling, and Final Quality Control. These activities illustrate essential tasks for successfully delivering final goods. For that reason, their automation and digitization can help the company attain business excellence.

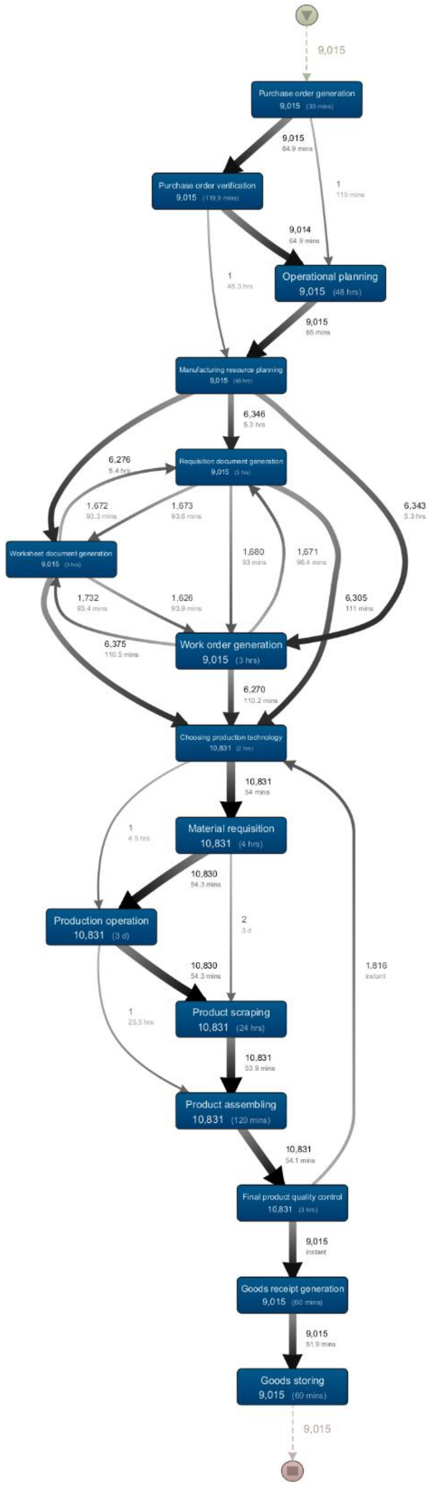


Fig. 3. Production planning frequency mining research results

### *B. Performance perspective*

Fig. 2 presents the performance perspective of the production planning process.

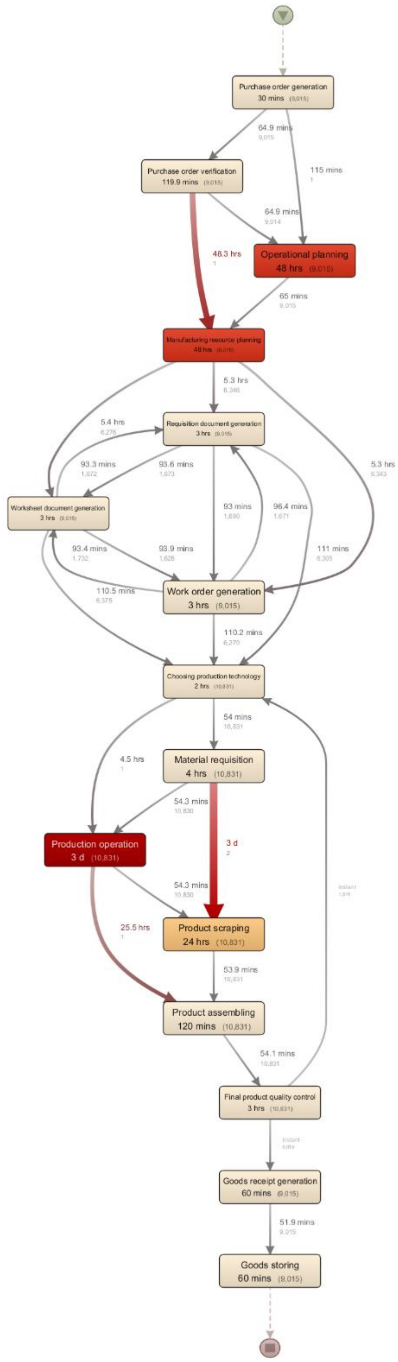


Fig. 4. Production planning performance mining research results

Numbers inside the rectangles indicate the mean duration of activities, while the numbers next to the paths connecting the activities represent mean waiting times. Activities with the longest mean durations are Operational Planning, Manufacturing Resource Planning, Production Operation, and Product Scraping. Furthermore, three bottlenecks are detected whilst analyzing mean waiting times – between activities Purchase Order Verification and Manufacturing Resource Planning, activities Material Requisition and Product Scraping, and activities Material Requisition and Production Operation. To handle these bottlenecks, the company should reconsider implementing automation and monitoring technologies. This could positively influence the production system's throughput and reduce long waiting times.

In addition to frequency and performance perspective analysis, the production planning KPIs were also studied in Disco. The production rate was studied using the *attribute* filter to count the cases where the **allocation ratio** was below 60%. Whether due to resource overloading or unrealistic planning assumptions, the results showed that 38% of cases, i.e., 3814, had an allocation ratio below 30%, while 5022 cases had an allocation ratio ranging between 30% and 60%. Only 179 cases had an allocation ratio above 60%. Fig. 3 presents a statistical overview calculated in Disco for the attribute *allocation ratio*, filtered to include only cases whose allocation ratio was above 60%.

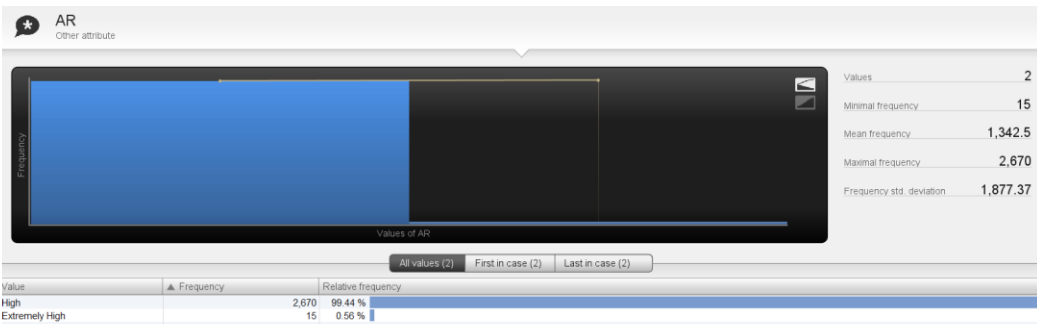


Fig. 5. A statistical overview of the allocation ratio

The production rate was also analyzed using the *attribute* filter to calculate the number of cases with low or medium **utilization efficiency**. The results showed that 36% of cases, i.e., 3624, had a low to medium utilization efficiency. Even though 90% of cases resulted in goods being stored, not all cases achieved optimal utilization efficiency. Hence, product storing might occur regardless of whether utilization efficiency is high or low.

The **throughput rate** analysis revealed that 2474 (24%) cases had low or medium production rates. On the other side, high **technical efficiency** was present in the majority of cases, 71% or 7199 instances. The mentioned results indicated a positive correlation between the production time and the busy time.

The **quality ratio** was also evaluated, showing that 11% of cases had a quality ratio between 30% and 60%. Fortunately, no cases with a quality ratio below 30% were detected.

The *attribute* filter in Disco was also used to calculate how many cases had a higher number of faulty products than initially planned, illustrating a higher **actual to planned scrap ratio**. A total of 5406 cases were extracted using this filter, i.e., 54% of cases, with the actual to planned scrap ratio above 60%. In some cases, the ratio even exceeded 100%. Therefore, the manufacturing company should perform root cause analysis to investigate the reasons for such results, monitor scrap rates and costs, and review equipment and other resources.

The results above demonstrate the relationship between the actual and planned number of faulty products. When exploring the ratio of faulty products to total produced quantity per unit time, no cases were detected with the **scrap ratio** above 60%.

When the *attribute* filter using Disco was applied to calculate the number of cases that have optimal performance indicators in terms of allocation ratio, utilization efficiency, throughput rate, technical efficiency, quality ratio, and scrap ratio, the authors reached the number of 38 cases whose every performance indicator was inside optimal levels. Fig. 4 illustrates a statistical overview of 38 cases recognized by Disco as having optimal KPIs, with a median case duration of 9.5 days.

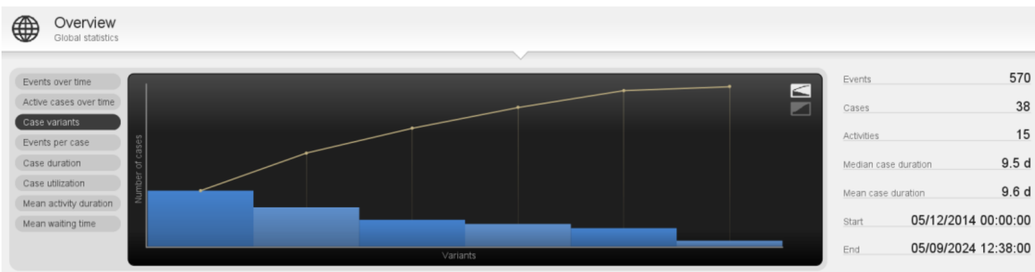


Fig. 6. Overview of cases with optimal performance indicators

Other performance indicators, such as **equipment load ratio** or **energy consumption**, can be studied using process mining techniques as well. Still, the existing event log lacks the information required for their calculation and should be subject to further adjustments.

*C. Organizational perspective*

Unlike Disco, ProM provides support for creating social networks as well [11]. Fig. 5 presents the social network generated in ProM using the *handover of work* metric. While nodes represent employees, arcs symbolize their mutual connections. Employees are ranked based on their impact on the production planning process, whereas employees positioned in the centre of the network have the highest ranking. Hence, the employees in the manufacturing department, along with the manufacturing planner and technologist, are most significant for successful production planning.

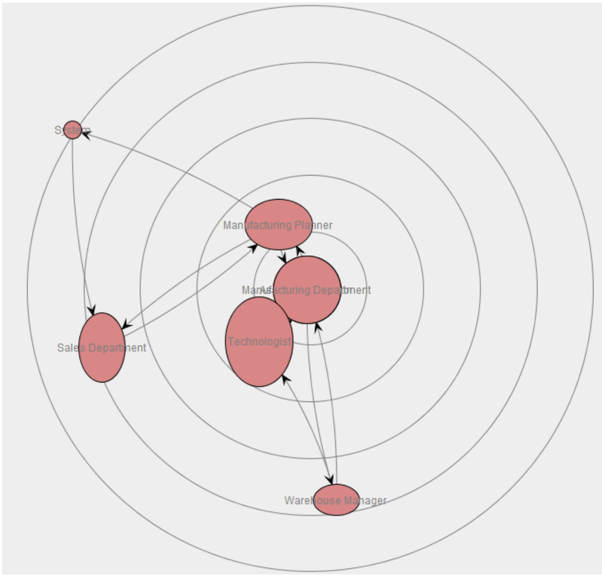


Fig. 7. Production planning social network

The common problem numerous companies encounter during production is resource overloading. To avoid such issues, the company should prioritize the most important tasks, assess resource capacities, and openly communicate with the employees. By investing time and effort in handling resource overloading, the company can improve productivity while reducing stress levels.

To achieve business excellence and improve customer satisfaction, the production planning process was thoroughly analyzed using PM tools – Disco and ProM. Such analysis provided valuable insights into the technical and organizational causes of production planning inefficiency, making it a promising method for further process optimization.

## V. Conclusion and Future Work

Process mining techniques were used to discover and study the production planning process map, including frequency, performance, and organizational mining. Frequency perspective analysis indicated essential tasks for successful production planning, such as material requisition and product assembling. The performance view of the production planning process revealed numerous activities with long waiting times, along with three process bottlenecks. Since such issues come with a high risk of decreasing efficiency and productivity, process mining is recognized as a method for their timely revealing. The paper also examined the handover of work, which provided insights into the key employees involved in process execution.

One of the key contributions of this paper is a KPI analysis relating to the production planning process, during which numerous performance indicators were analyzed using process mining tools. The research proved that more than half of the cases had low to medium performances, with the actual to planned scrap ratio being particularly critical. To overcome these problems, the company should perform root cause analyses and implement modern ICTs to automatically detect and monitor performance degradation. Additionally, identifying process bottlenecks can highlight specific parts of the production planning that can be subject to optimization.

Whilst previous research focused on automating the production planning processes, this research aimed to investigate how BPM and PM techniques can help companies analyze their business processes and perform KPI analysis. Combined application of Disco and ProM provided insights into frequency, performance, organization, and KPI perspectives of the production planning. As a result, this paper contributes to a better understanding of such processes, including challenges they may encounter. However, the event log used during this research was synthetically generated using Python. For that reason, access to real-time event logs could provide even more insights into process execution. The integration of BPM and PM in a real manufacturing company, whose event logs are automatically generated and stored by PAIS, represents a potential future work and the continuation of this research.

The combined application of BPM and process mining tools, such as Bonita, Disco, and ProM, presents a modern solution to frequent issues in the manufacturing industry, especially in the domain of production planning business processes. Process mining can enhance the BPM lifestyle by enabling process redesign, which leads to a more adaptive and dynamic environment [17]. Their successful integration can bring significant benefits for manufacturing companies and their customers, including process automation and digitization, reduction of long waiting times, resource optimization, etc. Introducing such changes can then help manufacturing companies improve their competitiveness in the business market.

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