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Process mining for maintenance purposes

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Abstract: In production-related sectors, maintenance is a critical element of operational efficiency. This paper examines the evolution of process mining. This technique utilizes event data to analyze and optimize real-world business processes, specifically focusing on its application in the context of maintenance objectives. Introducing a systematic approach, the methodology enriches maintenance event logs with contextual depth and goes through phases such as data preprocessing, process exploration definition, and performance analysis. The article highlights the central role of process mining in maintenance but also delves into its implementation's significant challenges and limitations. The article also provides key considerations for organizations considering process mining in their maintenance strategies.

Key-Words: Process Mining, Maintenance, Optimization, Event Logs, Data-driven Maintenance

Contents

1. Introduction

Ensuring the reliable and cost-effective maintenance of equipment and systems is a critical challenge across numerous industries. Unexpected breakdowns can significantly disrupt production schedules, leading to financial losses. Minimizing downtime, optimizing resource allocation, and maximizing equipment uptime while controlling costs are essential to achieving this goal. However, traditional, reactive maintenance approaches often fail, addressing problems only after they arise.

This is where process mining emerges as a powerful tool. Process mining is an innovative technique that utilizes event data generated by various information systems within an organization. By analyzing this data, process mining can uncover valuable insights into how real-world processes, like maintenance activities, are performed. This allows for informed decision-making and a proactive approach to maintenance management.

This paper delves into the dynamic intersection of process mining and maintenance, exploring the potential synergy between the two. Process mining, a powerful tool, aims to discover, monitor, and improve actual processes by extracting valuable insights from event logs embedded within today's information systems [Aalst 2011]. This in-depth data exploration offers a unique lens through which maintenance practices can be scrutinized and elevated. Aligning with this, the AFNOR NF-X 60 000 standard defines maintenance as "all activities aimed at maintaining or restoring an asset in a specified state of operation to establish a required function." Here, we see a clear connection between the broader goal of reliable and cost-effective maintenance and the granular insights that mining seeks to unveil. The intricate relationship between maintaining assets and understanding real processes becomes apparent as we navigate the nuanced landscape of process mining's potential applications in maintenance.

Research into process mining for maintenance is still underway [1] [2]. Still, the preliminary findings have already showcased the considerable potential of this technique in elevating both the efficiency and reliability of maintenance processes. However, it's essential to acknowledge the challenges associated with implementing process mining for maintenance purposes. Gathering and maintaining accurate and complete event logs from various sources within the maintenance process can be challenging, as they may be scattered across different systems and may not always be in a standardized format. Additionally, ensuring the data's reliability is crucial to avoid misleading insights from the analysis. This paper will answer the question: How can process mining be used to identify the root causes of breakdowns and improve maintenance planning?

In this comprehensive review of process mining for maintenance purposes, different sections will be navigated to uncover the impact of maintenance and process mining. In the background, the roots and evolution of maintenance and process mining will be delved into, aiming to understand their relevance better. They are moving on to the structured process mining method, outlining the critical stages. Then, we'll shift focus to the role of process mining in maintenance. Finally, a discussion section will be presented.

2. Maintenance

Equipment breakdowns are closely related to inspection, repair, and costs resulting from lost production or underutilization of equipment. Maintenance has a direct impact on a business or activity's operational performance [3]. Breakdowns affect system performance, safety, environmental impact, quality, customer service, competitiveness, or unit costs.

The extensive literature on maintenance practices identifies three general types of maintenance [4]. These classifications provide a conceptual framework for understanding different approaches to maintaining machinery and equipment. By delving into the nuances of each type, practitioners and decision-makers can make informed choices based on the unique requirements of their projects or operating environments. Recognizing these common types of maintenance highlights the importance of strategic thinking and adaptability in the maintenance process, acknowledging that one approach cannot lead to optimal results in all scenarios :

1. Corrective maintenance involves carrying out repair work in response to equipment or machine failures. The equipment operates until it fails when it is repaired or replaced. This approach is associated with drawbacks such as fluctuating and unpredictable production, a high percentage of defective products, waste accumulation, and frequent maintenance interventions caused by catastrophic failures [5].
2. Preventive maintenance is characterized by planned maintenance interventions to avoid machine breakdowns or stoppages. This approach relies on manufacturers' manuals and heuristics to guide its execution [6].
3. Predictive maintenance is based on using indicative values to anticipate impending failure. This maintenance type aims to deal with machine problems proactively before they become more serious. The aim is to intervene before damaging events occur to minimize downtime and optimize plant performance [7].

A well-designed maintenance policy is essential to optimize personnel, equipment, spare parts, tools, etc. Maintenance costs depend not only on the maintenance team but also on the actions taken by the operators and/or plant designers.

The technologies used by the maintenance function are constantly evolving, and new applications are being looked for to avoid performance degradation.

Maintenance teams must choose the most cost-effective techniques for each situation. This might involve preventive maintenance tasks like lubrication or filter changes or utilizing predictive maintenance techniques like vibration analysis to identify potential issues before breakdowns occur. The wrong decision in this respect can lead to new problems and possibly exacerbate existing ones. To avoid unintended consequences, it is essential to tread carefully down the open road of technological breakthroughs in maintenance.

The maintenance process is a multifaceted task involving the seamless integration of maintenance and process engineering functions, especially at critical stages of machine and equipment selection and application. This integration goes beyond simple reactive measures, including proactive actions directed at machinery and equipment. These proactive measures involve a combination of preventive and predictive maintenance strategies such as risk-based scheduling, condition-based maintenance, data-driven optimization, and Utilizing AI and Machine Learning [8]. Furthermore, dynamic projects require an open attitude to change, recognizing its potential impact on the overall maintenance system.

3. Process mining

In the realm of process mining, a relatively new research domain situated at the intersection of business process management and data science [9], various studies have contributed to laying the groundwork for investigations into the extraction of insightful knowledge from event logs [10]. While many researchers agree on the fundamental purpose of process mining as the extraction of information, particularly process models, from event logs [10], some argue that it represents a novel approach that bridges process modeling, computational intelligence, and data mining [11].

Process mining is a toolbox with methods to understand how things get done. It uses data to create a record of each step in a process (event log generation). Then, it can analyze this data to uncover how the process works (process discovery) - often different from the planned blueprint. This discovered model can be used to improve the blueprint or create a new one from scratch (process enhancement). Finally, process mining can compare the actual process with the planned one (conformance checking) to see where things veer off track [12]. This helps identify areas for improvement, as illustrated in Figure 1

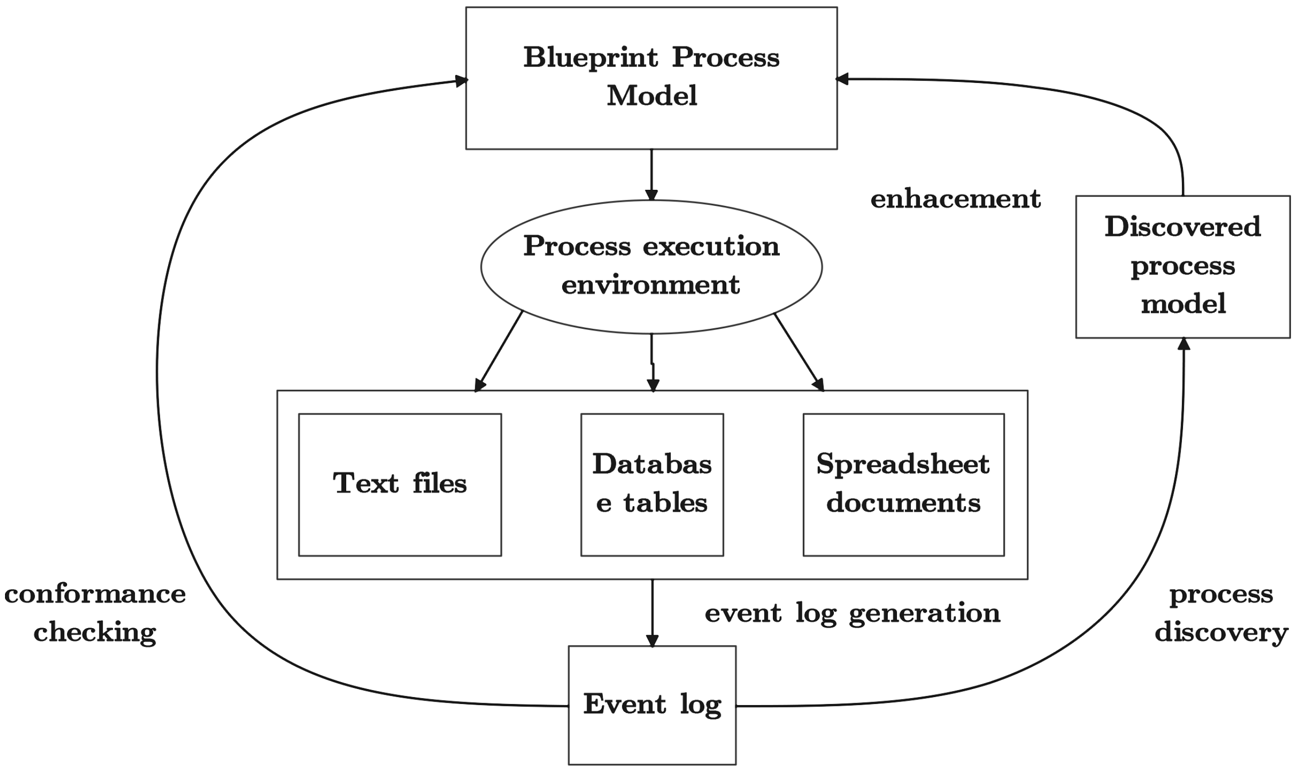

Figure 1: Process mining overview

Building upon established methodologies, researchers have adapted diverse techniques to explore the vast data generated by modern information systems [13]. Numerous studies have examined the relationship between data-driven performance measurement and process-centric analysis in process mining [2]. This diversity in research methods underscores the complexity of the field and highlights the need for comprehensive literature reviews [14].

There are different opinions on how things like how long activities take, how closely people follow the process, how consistent things are over time, and how quickly things wear out affect businesses. This can be seen by the different methods used in past studies [15]. In the past, research focused on how much people followed the planned process [14]. More recently, studies have shown how process mining can be used to uncover problems with processes, figure out why they happen, and improve them [2].

Recent studies have broadened the scope of process mining beyond just improving existing business processes. While research has shown its effectiveness in uncovering and fixing problems within business workflows [2], process mining can also be applied to software maintenance. This broader application offers a more holistic perspective on its capabilities. In software maintenance, process mining can analyze task execution logs, which can be particularly valuable. However, this also underscores the complexity of the field and the need for further exploration of its potential applications [16] [14].

Now, we will present a systematic process mining method to analyze process performance in the context of maintenance activities. The methodology consists of three basic steps: data preprocessing, scoping for process mining, and process performance analysis, as shown in Figure 2.

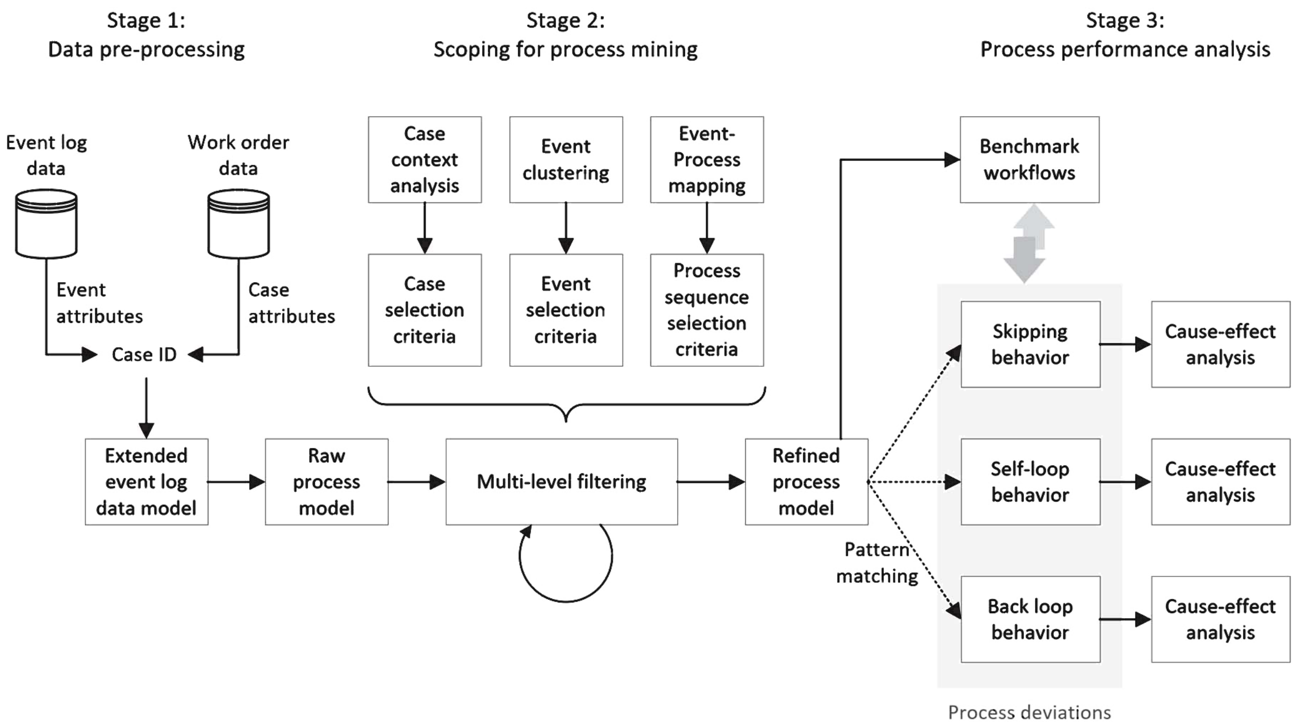

Figure 2: Overview of the process mining method

3.1. Data Preprocessing

The first phase of the proposed approach is data preprocessing. This phase aims to link process performance information and prepare input data for process mining. This phase begins with collecting event log data and work orders [2]. Maintenance activities in complex production systems are often performed as work orders, with the maintenance data stored in a computerized maintenance management system (CMMS) [17]. The maintenance event log data in a CMMS contains the essential attributes of the events of a maintenance workflow recorded in each work order, including the activity related to a particular event or state, the timestamp of when the event started and/or ended, and the case ID linking a series of events to a specific work order. In this document, the sequence of a series of activities of a particular case ID, ordered by a timestamp, is referred to as a workflow. Each case ID has exactly one workflow, while the same activity may occur several times in the workflow.

Maintenance event log data provides the minimum attributes required for process exploration. Data cleansing is necessary to remove entries that do not have any of these essential attributes. Maintenance work order data contains a number of attributes recorded at the case level, including contextual factors and characteristics that potentially impact the maintenance process's performance, such as production facility, work order type, equipment type, and maintenance personnel. Contextual attributes relevant to the process's performance are recorded along with the corresponding case identifiers. These attributes are not necessary for process extraction but allow contextual root cause analysis if mapped to individual process instances [18]. This mapping can be achieved by combining event log and work order data into a single data model, with the case identifier serving as a shared key for both data sets. The extended event log data is then exported from the data model and used to create a raw process model.

3.2. Scoping for Process Mining

The initial process model created in Step 1 includes all the essential details needed to discover the process and verify its conformance. However, understanding and interpreting the unrefined process model, mainly if it contains many events and routes, is problematic. To obtain concise and clear visual representations, it is essential to establish appropriate filtering rules. The main objective of the second phase is to delimit the scope of the process exploration, which allows for prioritizing crucial performance observations in the process model. As described in [12], critical elements of an event log can be identified at the level of events, cases/instances, and process models. At the same time, in the scoping stage, filtering rules are defined at the level of cases, events, and process models, with each level corresponding to a specific stage that facilitates the configuration of selection criteria.

3.2.1 Case Context Analysis

Case Context Analysis is performed at the individual case level to identify fundamental differences in the work process based on case-specific attributes. These attributes may include differences between preventive and corrective maintenance management procedures or between planned and urgent work requests. Since performance bottlenecks and causes of process deviations vary considerably between these workflows, combining them in a single process model complicates the analysis and can lead to fragmented results. For this reason, case attributes that involve inherent differences between workflows need to be examined separately. Case selection criteria are established based on the attributes identified in the contextual case analysis.

3.2.2 Event Clustering

Event clustering, done at the event level, directly influences the complexity and readability of the process model by reducing the number of separate activities. Some activities, primarily entirely dependent and highly automated, contribute little to the performance analysis. Entirely dependent activities occur exclusively between two specific activities, and the system executes highly automated activities with minimal time consumption. By grouping these activities with those that precede them, especially those with little importance in performance, process-visualizations can be rationalized without significantly affecting performance analysis. However, the choice of grouping can affect the study results, and it is critical to recognize the limitations introduced by grouping. Clustered activities are hidden in the process model, and their duration is embedded in the trajectories connecting neighboring activities. It should be noted that the event selection criteria do not reduce the number of cases included.

3.2.3 Event Process Mapping

Event process mapping at the process sequence level focuses on identifying critical event sequences in all workflows. This mapping enables incomplete or abnormal workflows containing inaccurate data to be excluded from the performance analysis. The initial step is to link the event grouping activities to four generic maintenance processes: planning, scheduling, execution, and shutdown [17] [19]. The essential events are then selected and organized to represent the sequence of the generic maintenance process, where one activity must be followed directly or indirectly by another in the same order of work. These defined process sequences form part of the selection criteria. Step 2 concludes with developing multi-level filtering rules, covering the case, event, and process sequence levels. The process of delimiting process mining is iterative and considers the refined model's complexity and readability.

3.3. Process Performance Analysis

The refined process model includes workflow variations relevant to process discovery and compliance checking, with a comprehensive assessment of maintenance process performance covering effectiveness, efficiency, and compliance [20]. Process discovery primarily helps measure effectiveness, efficiency, and compliance with external and internal standards. In the compliance domain, the analysis focuses on checking the conformity of process deviations, while the efficiency domain focuses on time-based measures in process discovery.

At the beginning of the process performance analysis, benchmark workflow variants that represent ideal scenarios are defined. These benchmarks can be modeled using BPMN tools [1] or selected from existing workflows. In the second step, efficiency bottlenecks are identified by calculating the workflows' waiting time and activity duration corresponding to the reference variants. Process deviations such as omissions, self-loops, and loopbacks are determined and assigned to the reference variants in the next step. For clarity, only workflows with only one type of deviation are selected. In the last step, the cause-effect analysis uses the case attributes from Step 1 to identify contextual features related to process deviations. This analysis helps to identify potential causes and facilitates the implementation of process improvements by maintenance managers [20]. Figure 4 shows the process models created in the second step, including the reference workflows and those with a specific process deviation. This visualization aids in understanding the structure and relationships between benchmark workflows and those with particular process deviation behaviors.

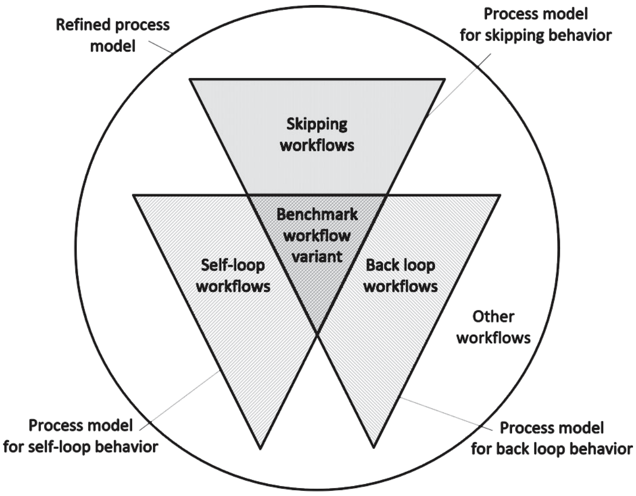

Figure 3: Modeling of a benchmark workflow variant and associated deviated workflows [2]

4. The Role of Process Mining in Maintenance

The application of process mining to maintenance involves using event logs generated by maintenance activities to obtain information about maintenance processes' performance, efficiency, and compliance aspects. Process mining focuses primarily on discovering, monitoring, and improving real-world processes by extracting knowledge from these event logs [10] [13].

An essential application of process mining in maintenance is the identification and analysis of performance bottlenecks. Event logs can be analyzed to assess the duration of process instances, individual tasks, and the time between task transitions, enabling a comprehensive measurement of maintenance process performance [10]. With this analysis, inefficiencies and areas for improvement can be identified, contributing to the optimization of maintenance processes [2]. Process mining can also help verify regulatory compliance by comparing observed maintenance processes with regulatory models to ensure compliance with established standards or regulations [13]. This coincides with the broader definition of compliance, which includes compliance with laws, requirements, expectations, or specifications [13].

In addition, process mining can uncover specific process models for maintenance activities. Analyzing sequential events recorded in event logs allows it to discover underlying patterns, deviations, and variations within maintenance processes [13]. This detailed process model can be used to visualize, understand, and communicate the complexity of maintenance processes [2].

In the context of maintenance performance analysis, process mining is a powerful tool for understanding the relationships between different factors such as resource utilization, abnormal behavior, and cost impact [10]. It is a data-driven approach to analyzing the large amounts of data generated by maintenance activities and provides valuable information for decision-making [21].

This review explores the growing application of process mining in maintenance practices across different industries. To illustrate its potential, we will delve into three case studies: the first examines how process mining can streamline workflows and identify bottlenecks in wind turbine maintenance [13]. The second explores a structured approach to process mining for measuring maintenance performance in the critical offshore oil and gas industry [2]. Finally, the third case study investigates using shop-floor data and process mining for preventive maintenance management, focusing on its integration with predictive models for optimal maintenance scheduling [22].

Case study 1 : Optimizing Wind Turbine Maintenance :

This study by Li Du, Long Cheng, and Cong Liu delves into the application of process mining for analyzing wind turbine maintenance processes [4]. The authors focus on three critical workflows: invoicing, extension, and acceptance. By analyzing event data collected from a real-world wind turbine maintenance system, the study employs process mining techniques to identify areas for improvement. The findings highlight the presence of redundant loops within the workflows, which could be eliminated to simplify and streamline the maintenance process. Additionally, the study identifies performance bottlenecks that can be addressed to expedite maintenance activities. This case study underscores the ability of process mining to optimize wind turbine maintenance for increased efficiency and cost savings [13]. Furthermore, process mining can be a valuable tool for preventative maintenance strategies. By analyzing historical maintenance data, wind farm operators can predict potential issues and schedule maintenance before breakdowns occur, minimizing downtime and maximizing wind turbine productivity.

Case study 2 : Structured Process Mining in Offshore Oil and Gas :

The second study explores a structured approach to process mining specifically designed to measure maintenance performance in the demanding environment of the offshore oil and gas industry [2]. This research highlights the limitations of traditional data-mining techniques, which often struggle to provide a comprehensive picture of how maintenance processes actually unfold. In contrast, process mining offers a more nuanced perspective by analyzing the sequence of events within a process. The authors propose a process mining framework that leverages event data extracted from a company's enterprise resource planning (ERP) system, a central hub for much of the data generated during maintenance activities. This framework encompasses three key types of analysis: process discovery, conformance checking, and enhancement [2]. Process discovery unveils the actual flow of the maintenance process, potentially uncovering deviations from the planned procedures. Conformance checking then compares this discovered process against the ideal scenario, highlighting areas where inefficiencies may be lurking. Finally, the enhancement stage utilizes the identified bottlenecks and deviations to propose targeted improvements. The case study demonstrates the power of this approach, revealing valuable insights into process bottlenecks, scheduling inefficiencies, and rework occurrences within the maintenance process. This allows for data-driven decision making, enabling operators to focus improvement efforts on the areas with the greatest potential payoff. Ultimately, by optimizing maintenance processes, this approach can significantly enhance maintenance performance and equipment reliability in the offshore oil and gas sector, leading to increased production uptime and cost savings [2].

Case study 3 : Shop-Floor Data for Preventive Maintenance :

The final study focuses on utilizing process mining for preventive maintenance management in the fast-paced environment of a shop floor [22]. This research proposes a three-stage approach specifically designed to optimize maintenance processes. The first stage, data preprocessing, ensures the data used for analysis is accurate and consistent. Imagine a scenario where maintenance records lack timestamps or contain errors - process mining would be analyzing faulty information, leading to misleading recommendations. The second stage, scoping, involves defining the specific maintenance process segment under scrutiny. This targeted approach allows for a laser focus on potential bottlenecks, avoiding the distraction of irrelevant data. Finally, the third stage, performance analysis, leverages various process mining techniques to identify areas for improvement [22].
The case study analyzes a real-world corrective maintenance scenario, revealing inefficiencies within the scheduling and execution phases. These inefficiencies could involve delays in assigning technicians due to unclear communication or a lack of readily available spare parts. Understanding these bottlenecks is crucial for streamlining the maintenance process and reducing turnaround times

Table 1 compares the application of process mining techniques (e.g., process discovery, conformance checking) across these three case studies.

Feature	Case Study 1	Case Study 2	Case Study 3
Industry	Wind Energy	Offshore Oil & Gas	Manufacturing
Data Source	Real-world wind turbine maintenance system	Company's Enterprise Resource Planning (ERP) system	Shop-floor data
Process Mining Techniques	Process discovery, Conformance checking	Process discovery, conformance checking, enhancement	Process discovery, Performance analysis
Analysis	Identify redundant loops and performance bottlenecks	Identify process bottlenecks, scheduling inefficiencies, and rework occurrences	identify inefficiencies, and explore integration with predictive models for improvement
Outcome	Streamlined and efficient wind turbine maintenance process	Enhanced maintenance performance and equipment reliability	Proactive approach to preventive maintenance and optimal maintenance scheduling

Table 1: Case studies Comparison

These three studies collectively demonstrate the significant potential of process mining to revolutionize maintenance practices across various industries [13] [2] [22]. By providing a comprehensive view of maintenance workflows, identifying bottlenecks, and facilitating performance measurement, process mining empowers organizations to optimize maintenance processes, minimize downtime, and ultimately achieve greater efficiency and cost savings [13] [2] [22]. While challenges exist regarding data quality and standardization, the potential benefits of process mining are undeniable. As the technology continues to evolve, we can expect even broader adoption and further advancements in its capabilities to transform maintenance operations for improved equipment reliability and operational excellence.

5. Discussion

Often complex and dynamic, maintenance processes pose several challenges when using process mining. Multiple studies have emphasized the issue of event log quality [13] [10] [11]. To guarantee the dependability of these logs, it is crucial to meticulously account for issues such as duplicate entries, incomplete instances, and precise timestamps. The intricacy of maintenance tasks hinders data preparation and impacts the precision of the resulting process models.

Interpreting the generated process models is particularly important when dealing with unexpected executions, automatic loops, repetition situations, and skipped actions [13] [14]. To comprehend the practical consequences of these model components, one must strike a delicate equilibrium between the technical aspects of process retrieval and the operational intricacies of the maintenance process.

Identifying performance bottlenecks is a crucial result of process analysis. Nevertheless, firms may encounter challenges when attempting to derive practical implications from these findings [2] [15]. Analyzing the underlying factors and applying efficient solutions to enhance productivity can be challenging and require a profound comprehension of the service context. The continuous integration with pre-existing systems poses a persistent difficulty [15] [16]. Ensuring seamless interoperability is crucial to prevent any interruption in the data flow throughout the implementation of Process Intelligence. Companies must formulate a strategy to integrate this cutting-edge method with their current information systems.
To effectively utilize process mining for ongoing enhancement in maintenance processes, businesses should give priority to the following recommendations;

Establish rigorous data governance and quality control procedures to guarantee the precision of event logs utilized in process mining analysis [9]. [23]. Internal knowledge Development: Enhance internal knowledge by implementing focused training programs for staff engaged in process mining and maintenance optimization [15]. Continuous Improvement Mindset: Cultivate a culture of ongoing enhancement inside the organization, consistently refining process models using fresh insights from process mining [13].

Goal Setting and Stakeholder Alignment: Establish explicit objectives for process mining projects and guarantee the active participation of relevant parties, linking the project with broader company goals [15].

Performance Bottleneck Reduction: Employ proactive measures to eliminate and diminish performance bottlenecks identified through process mining analysis [2]. Comprehensive Staff Training: Deliver extensive training to staff on the implications of process mining findings, guaranteeing comprehension and optimizing the advantages of this innovative approach [14].

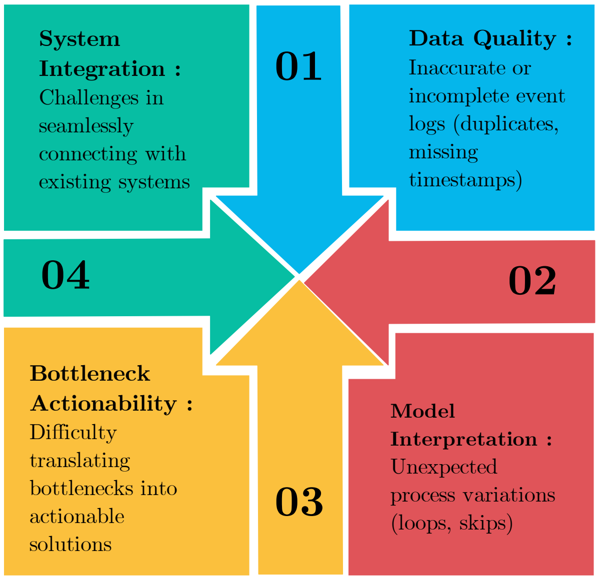

Figure 4: Challenges of Process Mining in Maintenance

6. Conclusion

In conclusion, this article has delved into the structured process mining approach for maintenance activities, shedding light on its potential benefits and challenges. Examination of the role of process analysis in maintenance has demonstrated its ability to provide detailed information on performance and compliance. However, the challenges and limitations identified highlight the importance of ensuring data quality, developing capabilities, and fostering a culture of continuous improvement within organizations. When navigating the process maintenance landscape, the considerations outlined for implementing process intelligence provide a roadmap for organizations to harness the potential of this technology. Integrating process analytics into maintenance practices promises to improve productivity and profitability and a better understanding of the complexity of operations. By carefully examining these aspects, companies can pave the way for a future in which process analytics becomes an indispensable tool for optimizing maintenance operations.

Looking ahead, the next step is to experiment with this technique (process mining) in a real-world setting. The final engineer project will focus on applying process mining to a specific maintenance process within an industrial environment. This practical application will offer valuable insights into the feasibility and effectiveness of process mining for optimizing maintenance operations in the field.

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