Application of Process Mining Techniques to Support Maintenance-Related Objectives

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Abstract. The variety of data types generated in manufacturing environments leads to a situation where data-driven approaches for analytical maintenance support no longer have to be limited to the equipment level, but rather can be extended to further perspectives. To this end, this paper examines how process mining (PM) as an approach to extract knowledge about process-related relationships can be applied to support maintenance-related objectives. Our research is carried out by using exemplary data from a manufacturing company, where we successively take different data attributes from various source systems into account and apply selected PM techniques to demonstrate their applicability. As a result, we showcase how different insights can be provided, such as the analysis of a machine's internal behavior, examination of error dependencies across multiple production steps, determination of a machine's relevance within the equipment network or the discovery of bottlenecks regarding frequencies, cycle times and costs.

Keywords: Data-Driven Maintenance, Maintenance Objectives, Process Mining, Data Mining, Business Analytics

1 Introduction

In no other sector, more data are generated than in the field of manufacturing, ranging from process control and production status records to condition monitoring data of the overall equipment [1]. The variety of machine-generated data provides a vital asset for industrial maintenance, where approaches like condition-based maintenance (CBM) are applied for diagnostic and prognostic purposes to guarantee high reliability, low environmental risks and human safety [2-4]. Such approaches primarily focus on the equipment level and make use of data mining (DM) algorithms like clustering and classification techniques [5]. However, due to the diversity of manufacturing data, there are also other methodical approaches which allow a consideration from more distinct perspectives. Such further perspectives could be provided, for example, by applying techniques from the field of process mining (PM), where sequentially generated event data are utilized to extract hidden knowledge about process-related relationships and patterns [6]. In this way, it possible to obtain insights that are no longer based only on an instance level, but rather extend to an inter-unit consideration, making this approach also interesting for maintenance questions beyond a scope on the equipment level.

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While PM has already been applied successfully in various domains like transportation, healthcare, banking, retail or education [7], an application to the field of industrial maintenance is rather scarce within the current literature. For this reason, our paper aims to demonstrate its applicability within this particular context and addresses the following research question (RQ):

RQ: *How can process mining techniques be applied for knowledge extraction in manufacturing environments to support maintenance-related objectives?*

To carry out our research, we used exemplary data records from a manufacturing company, where we successively took data attributes from various source systems into account and applied PM techniques derived from the literature. Following this approach, the remainder of this paper is structured as follows: In Section 2, we provide the conceptual background for both disciplines of interest. We then showcase the applicability of PM techniques to support maintenance-related objectives in Section 3. Finally, we draw a conclusion and give an outlook for further research in Section 4.

2 Conceptual Background

2.1 Industrial Maintenance

Industrial maintenance can be understood as a broad field with many accentuations and facets. Therefore, a consideration of various maintenance definitions is required to derive central objectives for which analytical approaches based on different data assets can provide a methodical contribution.

In general, maintenance can be defined as a combination of all administrative and technical activities that are required for preserving the desired operating condition of the production equipment [8]. This statement can be extended by the British Standard Institution including the activities to restore the operating condition of production equipment [9]. Likewise, the guarantee on plant availability as well as part of the plant safety through resilient systems are connected to those objectives [10, 11]. Additionally, the DIN EN 13306 includes the aspects cost efficiency, environmentalism and product quality [12]. [13] augments this list with the efficient use of resources, which have divergent manifestations. Thus, [14] distinguishes "main resources" and "other resources". Conclusively, the Maintenance Engineering Society of Australia announces "(…) that maintenance is about achieving the required asset capabilities within an economic or business context" [15] and specifies the optimization of production equipment as another aspect of maintenance. As a result, nine different core objectives of maintenance can be extracted as listed in Table 1, which will be referenced in the following by referring to their respective objective identifier (OID).

The actual maintenance execution is then carried out via different programs like time-based or data-driven concepts [2, 4], whereas our focus is on a data-driven support. Given the strong emphasis on the equipment level, the majority of data-driven concepts like CBM or predictive maintenance primarily concentrates on a particular unit of interest and thus employs classical DM techniques from statistics and machine learning [5]. This includes, for example, cluster analyses to detect unusual machine behavior, classifiers to determine heterogenous fault modes or artificial neural networks to predict a machine's remaining useful life [4, 5, 16]. However, due to the diversity of generated data in manufacturing environments, it is also possible to establish further analytical perspectives. As specified by our research goal, this will be demonstrated by applying techniques from the field of PM.

Table 1. Core Objectives of Industrial Maintenance

OID	*Objectives*	*References*
O1	Increase of machine lifetime	[8-11]
O2	Optimization of production equipment	[15]
O3	Retention or increase of product quality	[12]
O4	Minimization of machine downtimes	[8-11]
O5	Guarantee of safety	[10]
O6	Reduction of risk of failure and damage	[8-11]
O7	Efficient use of resources	[10, 13, 14]
O8	Retention of environment protection	[10, 12]
O9	Increase of cost efficiency	[12-15]

2.2 Process Mining

PM is characterized as a young research area that has been researched in the information systems domain in the last decade and established as a connection between business process management on the one hand and data science/business analytics on the other hand [6]. In general, PM tries to gain, aggregate and visualize both company- and process-relevant information by evaluating and analyzing great amounts of data in the sense of so-called event logs. Up to now, PM has been used in diverse fields like retail, education or healthcare, thus showing wide application areas. For example, while [17] and [18] use PM for the maintenance of web pages and their optimization and improvement, [19] tries to achieve personalized learning based on students' performance data. Furthermore, [20] show how PM can be used to identify deviations in healthcare processes from existing policies and best-practices, whereas [21] show a possibility to use PM to discover the customer fulfillment process in a telecommunication company.

Overall, there are three components of PM, each specialized on one remit. First, *process discovery* handles the creation of process models that are representative in behavior towards the underlying event logs. Hence, process discovery can be seen as the most relevant but also most difficult task of PM and offers many possibilities because of divergent process perspectives, such as the organizational or time-based perspective. By contrast, *process conformance checking* focuses the conformity of process models with the operative behavior observed within the event logs [6]. The aim of this comparison is to detect similarities, differences and deviations to evaluate "if actual processes follow prescribed behaviors or rules" [22]. As a last type of PM, the extension of existing event logs by additional attributes is characterized as *process enhancement*. These attributes define new perspectives and analytical possibilities in and on the process, whereby PM is opened for potential adjustments to reach subjective goals [6].

3 Maintenance Support with Process Mining

The following section demonstrates the applicability of PM towards the support of maintenance-related objectives. For this purpose, exemplary anonymized data from a manufacturing company producing car tires were used. The production process extends over various steps that are carried out on distributed machines. For the application of PM techniques, data from different source systems had to be brought into a standardized event log structure [6]. Here, we started with the minimum of required attributes at the lowest level and then successively considered additional attributes and levels to apply further perspectives. Relevant data were extracted from systems at different application layers, such as energy meters, programmable logic controllers, a manufacturing execution system (MES) or an enterprise resource planning system (ERP). For demonstration purposes, data samples from all systems were filtered and strongly simplified. Thus, the focus was primarily set on the overall feasibility instead of quantitively evaluating specific scenarios with regard to the current status and possible improvements.

3.1 Starting with the Minimum of Required Data

The minimum required data for PM is defined by the existence of two attributes: i) an *activity* that refers to an event class of interest and ii) a *case ID* that relates each event to a particular process instance. Since most PM tools also require a *timestamp* to ensure the event order, this attribute was integrated as well. With this basic data, it was possible to perform *process discovery* to investigate procedural structures at different levels [6].

At the lowest level, process activities can be defined by events derived from different machine components like logical elements, transistors or switching circuits. This allows to track consecutive states of a single machine and derive insights into a system's internal behavior without considering the entire production process. Thus, irritants like a high number of skipped events in machines or increased operation time can be detected at an early stage to trigger proactive maintenance actions and prevent further damage.

At a next level and this will remain the primary focus in the following considerations, process activities can be defined at the scope of the actual manufacturing process with all its steps and sub-steps mainly derived from MES data. This leads to multiple advantages as it becomes feasible to analyze the entire manufacturing setting regarding frequencies and durations of steps/sub-steps as well as variants, whereby one variant describes a specific path through the production process [23]. As a result, bottlenecks, time per step or variant and many other process statistics can be evaluated.

In an analogous manner, it is also possible to examine event data generated by the execution of maintenance tasks. This allows to reconstruct and critically analyze the procedures of operational maintenance activities. However, since most maintenance tasks are still executed manually without leaving extensive digital traces - as in the particular case where only scarce information could be extracted from the ERP - the focus will remain on the investigation of existing machine and production data.

Subsequent to the discovery of process structures, the results can be used to realize the *process conformance checking,* following [6]. As already stated, this allows to explore deviations and commonalities between the intended/documented processes on the one hand and the real as-is processes on the other hand. Moreover, it is possible to determine if specific process steps exceed predefined control limits like excursion rates, cycle times or a predefined amount of process instances to run on one single machine.

Overall, in terms of the maintenance objectives regarding machine lifetime (O1) and equipment optimization (O2), all those insights can be used to reveal unintended behavior of the production process at different abstraction levels and thus help to schedule maintenance activities proactively to prevent machine failures. Furthermore, this methodical approach offers the possibility to validate performed maintenance actions and their impact by comparing the process performance before and after an intervention.

3.2 Including Machine Attributes to Enrich Process Activities

While in the preceding scenario the activities of the production process were primarily considered in isolation, the database can further be enriched with resource information in the sense of *process enhancement*. Therefore, the process steps to be explored are subsequently not only specified by the production activities, but also by the machines performing those activities. Thus, after the *process discovery*, it can now be observed that all process steps consist of activity/machine-compositions, as shown in Figure 1, where the first step *"PSc3e047c7"* is performed by the machine *"S_636gt"*.

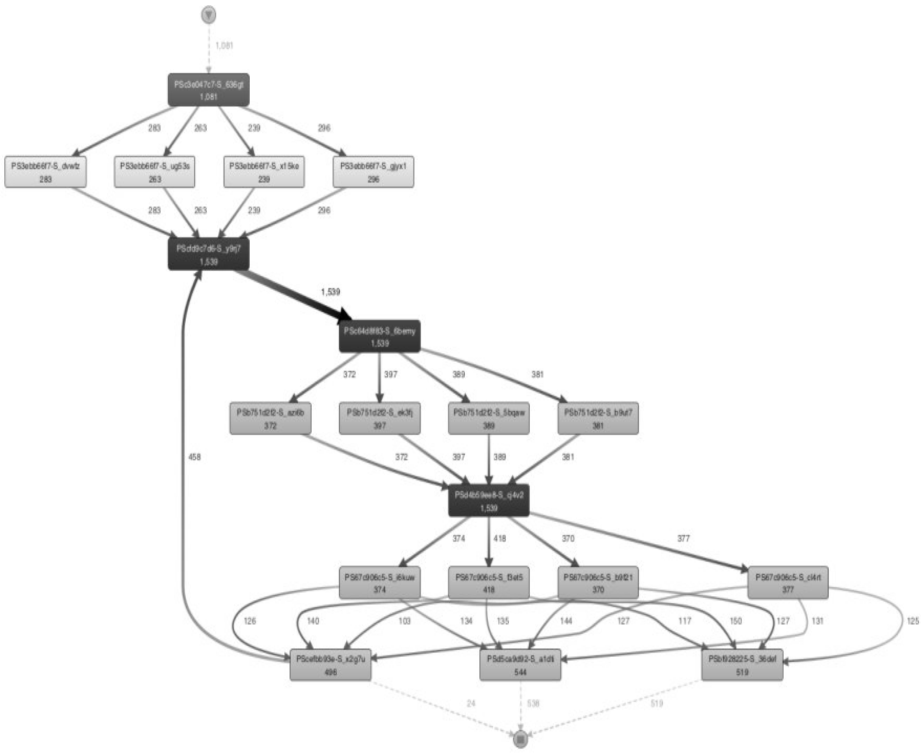

Figure 1: Simplified Production Process with Machine Data (Recorded in Disco)

With this representation, the workload of the machines can be expressed by frequency numbers and different color schemes indicating the different intensities. Thus, it is possible to detect machines with high workloads that are possibly more exposed to continuous stress. Those machines often occupy central positions within the production flow (like in the first, third, fourth and sixth step in Figure 1) and therefore require more attention to proactive maintenance, since a failure may disrupt the entire process (O4).

Similarly, the distribution of the workload between different machines performing the same production step can be examined. For example, the second step is executed by four different machines in parallel. However, while machine *"S_gjyx1"* was running 296 instances, unit *"S_x15ke"* was only executing 239 instances. In combination with scheduling information, these insights can be used for an optimal allocation of process instances to machines, with the goal to equalize the number of processed products (O2) and thus to lengthen the machines' lifetime (O1).

Moreover, by not only focusing on a single activity level but also considering their transitions, different process variants can be evaluated in terms of distinct production paths. Here, the activity/machine-composition offers the advantage to gather insights about sequential machine interdependencies. As such, it can be assessed, for example, whether some incidents primarily occur within process paths where certain machines were previously involved. This can also be relevant for quality assurance (O3), where specific machine combinations throughout the production flow may lead to different quality levels of the final product (c.f. Section 3.5).

Another perspective can be provided by analyzing durations of activities and transitions using timestamps instead of solely concentrating on frequencies. Analogously, time attributes can directly be incorporated in the process model to detect activity/machine-combinations with high cycle times in terms of bottlenecks and inefficiencies (O2). Simultaneously, exceptionally long cycle times are an indicator for faulty machine behavior to trigger further inspections and respective interventions.

3.3 Implementing and Expanding the XES-Lifecycle Extension

The exploration of failure events within the process is another relevant facet of maintenance support. For such a consideration, the given event log requires an additional attribute to document the production status of each step.

This can be implemented by employing the XES-Lifecycle Extension as introduced by [24], which provides predefined values like *"start"*, *"complete"*, *"suspend"*, *"resume"* or *"pi_abort"*, with the last value defining an interruption of the current process instance. It is conspicuous though, that with these values only the possibility is given to analyze interrupting machine errors and suspending errors. However, with regard to errors that do not interrupt the production process, this framework requires an extension. Thus, we created an additional state, called "*fail_complete*", to describe the completion of a process step while errors take place in execution. This allows to focus on failure events in the process analysis and generates high profit for subsequent analysis, such as tracking overall failure times. For example, the PM tool Celonis allows to define domain-specific key performance indicators (KPI) that can be monitored live during process execution. By using this feature in combination with the newly created state, KPIs for the number and the ratio of failure events in a single production equipment can be defined. This live-monitoring of the production process combined with the historical process data gives some indication of past and future machine behavior. For instance, this enables to determine the average number of internal errors until the process instance is finally interrupted by a serious error (O4).

Moreover, also the duration of failure events is of high relevance for maintenance. At this point, there are multiple ways to achieve the documentation of these downtimes. Enhancing the event log by inclusion of an additional attribute containing these data represents one way to accomplish this goal. However, this approach contradicts with one of the fundamental principles of PM, as the downtimes exhibit a direct reference to the processing machine and not to the activity. Another option arises when saving the desired information in an additional event log defining the production equipment as events. But this leads to a loss of the process perspective. Therefore, it's necessary to calculate the downtimes by using existing data and to add another dimension to the predefined time perspective. Based on the assumption that the downtime is calculated by the timestamps of the failure and the reactivation of the machine, the dead times can be computed by using the pseudocode depicted in Figure 2. In contrast to the previous approaches, this allows to view dead times directly in the process and to analyze them in case specific or cumulative way by using all advantages of *process discovery*.

```
# get_breaktime:
n = max(#CaseID)
FOR i=0 TO n-1 DO
  current_machine = #Machine(e)[i]
  current_LC_transition = #LC(e)[i]
  IF current_LC_transition == "stop" THEN
      FOR j = i+1 TO n  - 1 DO
          next_machine = #Machine(e)[j]
          IF current_machine == next_machine THEN
              #Starttimestamp(e)j - #Endtimestamp(e)i
          END IF
      END FOR
  ELSE
      continue
END FOR
```

Figure 2: Pseudocode for Calculating Downtimes

Apart from this, dependencies between different errors in the process are focused. For the discovery of such dependencies, different techniques from statistics and machine learning can be used, such as support vector machines or logistic regression [25]. Exemplarily, we use the logistic regression that allows to receive direct failure probabilities. Transferred to the present context, this enables to determine if the probability for a specific machine documenting an error increases, when another machine earlier in the process also documented an error. It could be found, for example, if station *"S_636gt"* documents an error, then station *"S_dvwfz"* is 2.56 times more likely ($B = 0.94, p < 0.001$) to also write an error in reference to the state in which station *"S_636gt"* would not have documented one ($X^2(1) = 23.84, p < 0.001$). In this way, failure dependencies in the process can be revealed and provided for decision support by directly visualizing this information within the process model.

This particular scenario illustrates the successful combination of PM and DM techniques. PM first aims at uncovering sequential patterns to identify process complexities and distinct paths. This allows the detection of discrepancies between the desired and actual process behavior, for example, in the form of anomalous paths, bottlenecks or deviating process performance. Once such discrepancies are detected, DM techniques can then be used to identify non-local and multi-causal effects that possibly span over multiple process steps [26]. Referring to machine failures during the execution of production processes, it is possible to determine patterns which classify a specific sequence of error events. Thus, the option arises to predict the breakdown of a machine based on the error events that occurred in previous stages, which allows to interfere in the process at the right time and to perform tasks to prevent upcoming machine failures (O1, O4).

3.4 Adding the Organizational Extension

Another perspective provided by PM is the organizational view, with the goal to extract and visualize social network structures between different entities involved in a process environment [7]. In this context, a social network consist of i) nodes representing organizational units and ii) relationships representing the connections between those units [6]. Transferring this approach to the current setting, the first part can be defined by the production equipment, whereas the second part is characterized by ingoing- and outgoing connections according to the manufacturing process. To achieve this kind of networks, the XES Standard defines the "organizational extension", encompassing the name or the ID of the respective operator in the event log [24].

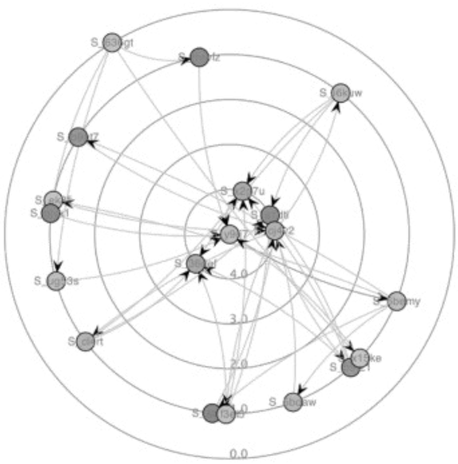

Figure 3: Network of Production Equipment (Recorded in ProM)

Besides the creation of a visual network (c.f. Figure 3), the machines can additionally be assessed according to their importance within the network using centrality measures. Following this, the most valuable machine in the network is characterized by the highest number of connectors [27]. Focusing on the reduction of risk and failure damage (O6), it can be concluded that theoretically station *"S_y9tj7"*, positioned in the center, is of high relevance for the production process, as its failure may influence different other machines which could lead to a high capacity loss. Nevertheless, this approach only indicates a high equipment relevance based on relations to other production equipment, whereas ramifications of failures, like emission of harmful substances, are not included in this risk estimation.

3.5 Integration of Domain-Specific Attributes

When executing production steps, machines usually consume different input resources like energy and materials while simultaneously producing waste and other by-products. As such, the event log can further be enriched with attributes in terms of measured values and specific KPIs to illustrate the resource flow at a machine and process level.

Data attributes can be gathered from various systems, as in the current case where power consumption was measured via energy meters and material flows were collected from the MES. However, event characteristics are generally not limited to those aspects, but rather can extend to any other subject of interest, such as further environmental indicators [28] or quality-related attributes [29].

The integration of attributes can be done in two ways: On the one hand, it is possible to simply add them to the event log by appending it as a property to the corresponding events. On the other hand, an explication of an additional extension to the XES-Standard is possible to achieve a certain level of standardization by specifying concrete definitions of the attributes in the extension definition. This also permits to create domain-specific extensions for a complete set of properties, which then can be in the center of further analysis with a predefined prefix for their identification [24].

Once the event log is enriched with further attributes, they can be examined at the different levels addressed previously, i.e. for i) the overall production process, ii) individual production steps, iii) individual machines, iv) activity/machine-combinations, or v) distinct paths. In this way, it is possible, for example, to monitor resource efficiencies (O7), but also to track material flows in terms of waste and harmful materials (O5, O8).

In addition, it is also advisable to not only consider each attribute in a univariate manner, but rather to analyze them in combination with each other along the entire manufacturing process. Here, the combination with DM techniques proves to be helpful again, where each attribute either serves as a target variable of interest or as an input feature to predict the respective output [26]. This makes it possible, for example, to determine the relationship between the final product quality, measured at the end of a process, and the machine and process attributes at each individual production step (O3).

3.6 Evaluating the Cost Efficiency

In a production process, there are many different types of costs that need to be regarded when evaluating the overall cost efficiency. Therefore, an individual cost model needs to be applied to determine which parameters to include to the event log. In the given context, the costs for one process activity e in the set of all process activities E will be calculated with $\#_{TC}(e) = \#_{EC}(e) * \#_{t}(e) * EP + \#_{MC}(e)$ with TC as total costs of event $e \in E$, EC and EP as energy consumption and its current price, t as duration and MC as material consumption. When enriching the event log with the not yet included (external) data, it is noticeable that, due to the event centric focus of PM, there is a loss of information or costs regarding the event transitions of the process model. These transitions also need to be regarded as they are in the time or frequency perspective of a process. It is conspicuous that there are costs like the energy consumption in standby mode of a machine, required energy to get in production ready state or the consumption for cooling down in the time between two process steps in a production process. In conclusion, there are costs right before and after executing a specific task that are not yet regarded by an event centric focus. By further adding the cost calculation at the start and end timestamp of a process activity, possibilities arise to determine these unregistered costs and to provide a cost perspective of the process. Therefore, the costs before activity execution can be determined by subtracting the costs at the start of an event $\#_{StartCosts}(e_i)$ from the costs at the end of the previous executed event $\#_{EndCosts}(e_{i-1})$, whereas the costs after execution are determined by the subtraction of all cost attributes of an event: $cae(e_i) = \#_{EndCosts}(e_i) - \#_{ActivityCosts}(e_i) - \#_{StartCosts}(e_i)$. Given these attributes, it can be stated that the overall costs of a transition ct between events can be calculated by adding the pre-execution costs of an activity to the post-execution costs of the activity before that:

$$ct(e_i, e_{i+1}) = cae(e_i) + \left(\#_{StartCosts}(e_{i+1}) - \#_{EndCosts}(e_i)\right) \mid e_i \succ \; e_{i+1} \qquad (1)$$

In conclusion, a cost perspective on the process can be realized that allows to gather all information available through *process discovery* and to achieve a long-term validation and possible predictions of future production costs. Therefore, cost referred bottlenecks and cost intensive areas of the process can be identified (O9). Moreover, by focusing on process variants, optimization potentials can be realized, e.g. by distributing process instances to less cost-intensive machines (O2).

4 Conclusion and Outlook

The goal of this paper was to demonstrate the application of PM techniques in manufacturing environments to support maintenance-related objectives. Using successively more data attributes from various source systems at different application levels, it could be shown how insights from multiple perspectives were achievable. This includes, for example, i) the discovery of a machine's internal behavior by tracking its consecutive states, ii) the identification of error dependencies across multiple production steps by combining PM with DM techniques, iii) the determination of a machine's relevance within a network by using organizational mining, iv) the examination of bottlenecks by analyzing different process levels (e.g., process paths vs. single activities) with regards to time, frequency and cost indicators, or v) the evaluation of a machine's input and output efficiencies based on domain-specific attributes. Consequently, all maintenance objectives (ranging from aspects like lifetime extension and equipment optimization to resource efficiency and quality assurance) could be addressed to some extent.

While the focus at this stage was mainly on the demonstration of the overall applicability and feasibility, future work will be devoted to a more detailed examination in the sense of a quantitative evaluation. As such, it is planned - in accordance with given confidentiality restrictions - to provide more details about the data samples in each analysis scenario and then quantitatively discuss the results of applied approaches. For example, such an in-depth consideration could be based on a large number of summary statistics and indicators on the recorded behavior of machines and processes, which are then compared with the expected results from technical experts to evaluate how the generated insights can be used for better decision support.

Likewise, further work will place greater emphasis on the necessary data preparation steps, as this was largely ignored in the current study. For demonstration purposes, different data samples were filtered and strongly simplified. However, the integration of different data attributes from heterogenous systems into a standardized PM event log structure has to be considered as a challenging task [6]. For example, most of the involved manufacturing systems provide required event data only as by-products, which then have to be selected and merged at an adequate abstraction level on which a process flow is to be analyzed. Similarly, specific event attributes like energy or material consumption are often not recorded by default for each individual machine at each single production step. The challenge is therefore to assign such attributes in the event log according to their cause, thus enabling more fine-grained analyses. Consequently, those and many other aspects still remain as data preparation challenges [30], that may considerably hinder a successful PM application. However, once these steps are taken, our study showed a possible direction for how PM can provide multi-perspective insights to support decision making in maintenance as well as manufacturing settings in general.

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