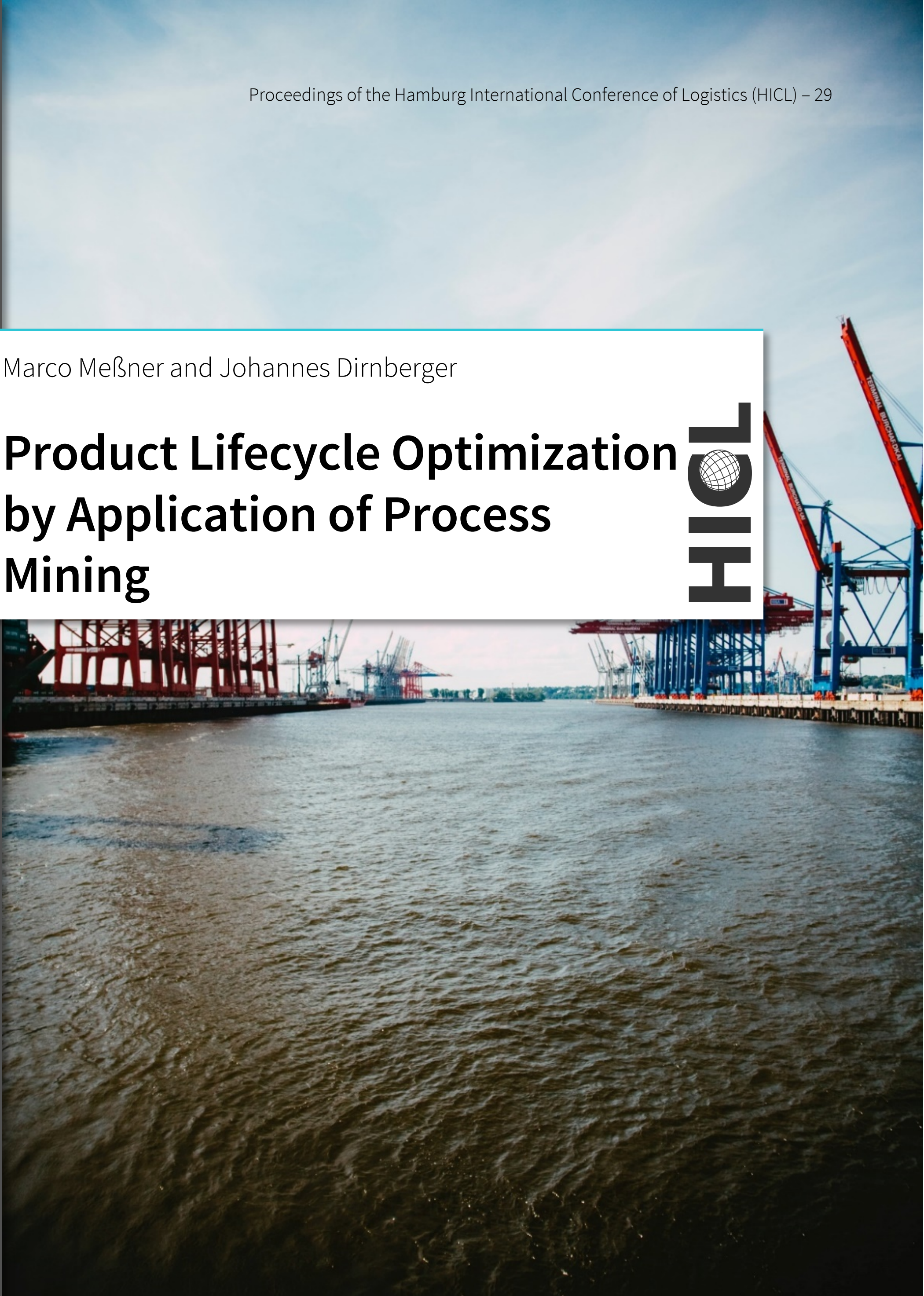

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Product Lifecycle Optimization by Application of Process Mining

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Purpose: Active product life cycle management contributes to supply chain optimization. However, in nowadays industry the high number of variants and backward loops complicate tracing the entire product lifecycle in an ERP system. Consequently, product lifecycle and corresponding process-organizational optimizations are difficult to implement using established analysis. The aim is to challenge process mining as an alternative to address these aspects.
Methodology: This paper, therefore, applies process mining to the ERP data of a component manufacturer in the metalworking industry. For this purpose, optimization potentials are derived from a literature research and subsequently validated by the application of process mining. Thereby, the data sample comprises 202 products with 15,000 corresponding activities, which were accumulated in the period 2017 to 2019.
Findings: Process mining reveals the product lifecycles and allows to take different analysis perspectives, such as a market or product category view. Firstly, potentials in a variant-driven business for PLM will be elaborated. Secondly, process-organizational recommendations for the product management are developed. Thus, this paper offers a concrete approach to mapping and analyzing the product lifecycle by application of process mining.
Originality: On the one hand, current analysis tools used in ERP systems merely assess the products actual status. On the other hand, PLM systems are regarded as costly due to the complexity but also a continuous process view is not its main focus. Nevertheless, there is little literature on alternatively using process mining in this context.

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1 Introduction

Effective data management is a prerequisite for large manufacturing companies that have to "handle considerable amounts of data" due to broad product ranges with numerous complex products that are tailored to the customer (Saaksvuori and Immonen, 2008, p.5.). One concept for meeting this challenge is Product Lifecycle Management (PLM) (Saaksvuori and Immonen, 2008, p.3.). Stark (2017, p.13) defines PLM as "the business activity of managing, in the most effective way, a company's products all the way across their lifecycles; from the very first idea for a product all the way through until it is retired and disposed of". Stark (2020, p.6) further specifies the phases that a product goes through in its life cycle from the perspective of a manufacturing company as *Ideation*, *Definition*, *Realization*, *Service* and *Retirement*.

The origins of PLM lie in the Engineering Data Management (EDM) and Product Data Management (PDM) of the late 1980s, where the aim was handling the increasing number of Computer Aided Design (CAD) drawings (Saaksvuori and Immonen, 2008, p.2). The objectives of PLM today, however, are strongly focused on process optimization for the purpose of financial performance, time reduction, quality improvement and business improvement as Stark (2020, p.17) shows. As examples of business objectives, he cites the extension of product life to increase revenues, reduce development costs, reduce time to market, reduce customer complaints and increase the product release rate.

Special systems exist to support PLM. However, there exist some challenges in this context. Before benefiting from a PLM system, the initial setup is the

first obstacle. PLM systems are complex and accompanied by certain dependence on the software provider, especially when problems arise. Furthermore, investment costs of around € 500,000, such as those incurred by an engineering firm with 220 employees, also illustrate a financial issue. (Hansen, 2008)
It finally turns out that the spread of PDM and PLM software is not yet as widespread as a telephone survey conducted in 2017 with 505 managers interviewed, from German industrial companies with at least 20 employees who are responsible for digitization in their company shows. While CAD software is used by 92% and 5% are planning to use it, only 41% use PDM or PLM software and only 8% are planning to use it. (Bitkom Research and Autodesk, 2017)
An alternative way to analyze product life cycles is to analyze activities, digital footprints, in the Enterprise Resource Planning (ERP) system, that are tied to the material master information. In an ERP System, materials are created, changed and used in system applications: In SAP, for instance, the material master is created using transaction MM01 (Frick, et al., 2008, p.59). The material status is then maintained in the basic data sheet and to remain with the SAP example, this is done in transaction MM02 (Benz and Höflinger, 2008, p.88). This status indicates whether restrictions exist for the usability of a material and what these restrictions are. For example, a material can be in development or a discontinued material (SAP Help Portal). Thereby, the selection options for determining the respective material status can be defined as company-specific. All those changes and activities that are executed in an ERP System are stored and allow to analyse product life cycles with ERP data.

However, in nowadays industry the high number of materials and backward loops complicate tracing the entire product lifecycle in an ERP system using established analysis. Therefore, product lifecycle and corresponding process-organizational optimizations are difficult to implement. Since process mining is already applied for other typical process analyses (e.g. purchase-to-pay or offer-to-cash) in an ERP system, it can be an effective alternative for life cycle tracking. The reason is that process mining allows to analyze large amounts of data from the ERP system in a chronological context, based on timestamps (Van der Aalst, 2011, pp.10-13). To examine the suitability of process mining for product life cycle analyses, the following research question arises in this paper:

Which optimization potentials can be identified by the analysis of product life cycles applying process mining on ERP data?

Therefore, the goal of this paper is to apply process mining in a practical use case on the data set of an industrial manufacturing company for the analysis of product life cycles, document the results and thus answering the research question. For this purpose, 202 materials that reached the end of the product life cycle have been selected from a manufacturer's make to order business model. The data comes from the ERP system SAP. The analysis is carried out with Celonis process mining software, which is accessible for academic purposes (Celonis SE, 2020).

2 Process Mining for the ex-post Analysis of as-is Processes

In order to optimize processes in companies, two steps must be carried out beforehand. First, it is necessary to know the processes. For this purpose, data regarding as-is processes is collected. This can be done, for example, by means of widely used methods such as observations, interviews, workshops or the analysis of existing documents or information from IT systems. Secondly, processes are systematically analyzed to identify weaknesses. (Brunner et al., 2017, pp.25-27 and 45f)

The process analysis is the decisive step in the preparation of decisions and, therefore, described in the following.

2.1 Process analysis

The systematic analysis of weaknesses is often done with checklists according to certain perspectives, which also help to identify the causes of problems that have occurred (Best and Weth, 2010, p.85).

These qualitative considerations are reviewed and supplemented by quantitative calculations and simulations. The quantitative process analyses can be divided into ex-ante, real-time and ex-post analyses, depending on the time of the process analysis. Real-time analyses as process monitoring, take place in real time, as the name suggests. Ex-ante analyses are performed before the actual process execution, for planning purposes. An example is process simulation with plan data. Ex-post analyses are carried out after process execution. This allows problem areas such as long lead times to be identified retrospectively. A well-known ex-post analysis method is process mining. (Kühn and Bayer, 2013, p.137f).

Van der Aalst (2011, p.8f) describes process mining as "the idea (…) to discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs readily available in today's systems". According to him, the process-relevant data is scattered across different Process Aware Information Systems (PAIS), such as classic ERP systems and many more. In view of analyzing the product life cycle, it is relevant, as described in the introduction, that the material status is maintained in the ERP system. The changes in the material status are the results of operative processes, which are documented in the ERP system. In addition, ERP systems directly provide the event logs relevant for process mining (van der Aalst, 2011, p.8f). For this reason, process mining is a suitable process analysis technique for retrospectively analyzing the actual life cycle of products, thereby uncovering potential for improvement in the processes. Thus, Process Mining is described in the following.

2.2 Process Mining

Process mining is a relatively young field. In the beginning, small amounts of data were available. Therefore, the algorithms were not very useful in practice. Currently, however, process mining is of great importance in process management theory and practice. (Van der Aalst, 2016, p.20)
Nowadays, the data available in PAIS support whole processes and not individual activities. In addition to ERP systems well-known representatives of PAIS are Customer Relationship Management (CRM) systems, Workflow Management (WFM) systems, Business Process Management (BPM) systems, call center software, high-end middleware and many more. These systems are aware of the process as the completion of one activity triggers

another activity, for example. Secondly, however, there are information systems that only execute individual steps in the process. These include, among others, database systems, mail programs or spreadsheet programs. These informations systems cannot be actively involved in the management or orchestration of the process, because they store process-relevant information in unstructured form. These information systems store process-relevant information in unstructured form. For example, event data is scattered over many tables. In such cases, event data does exist, but is required to be extracted. This data extraction is crucial for process mining. And to make this data from any operational process usable, process mining bridges the gap between data science and process science (Van der Aalst, 2016, p.27f and 32). Regarding process pining techniques, a distinction is made between three types: *Discovery*, *Conformance* and *Enhancement* (Van Der Aalst et al., 2011, pp.172-174).
Van der Aalst (2016, p.33) defines *Discovery* as a technique that "takes an event log and produces a model without using any a-priori information." Essentially, according to him this involves presenting and analyzing the actual process with all its variants. In terms of *Conformance* he speaks of a technique where "an existing process model is compared with an event log of the same process. Conformance checking can be used to check if reality, as recorded in the log, conforms to the model and vice versa. For instance, there may be a process model indicating that purchase orders of more than one million Euro require two checks. Analysis of the event log will show whether this rule is followed or not." Finally, *Enhancement* means to "extend or improve an existing process model using information about the actual process recorded in some event log. Whereas conformance checking

measures the alignment between model and reality, this third type of process mining aims at changing or extending the a-priori model. One type of enhancement is repair, i.e., modifying the model to better reflect reality" (van der Aalst, 2016, p. 33).

The current situation with regard to process mining shows that although it is an important prerequisite that the business processes are mapped in IT systems, incompleteness can be increasingly compensated for. Existing analysis tools can already reconstruct complete process flows from rudimentary or incomplete electronically recorded processes and thus create process models. (Hierzer, 2017, p.87)

At the same time, the selection of relevant data sources is still regarded as crucial for addressing current topics such as the integration of sensor-based, Internet-enabled devices in business processes (Thiede, et al., 2018, p.914).

Even if there are still challenges, the above definitions show the potential that process mining has in theory. Our goal is to use this potential and to apply process mining to a product's life cycle. The use case implemented with real-world data is described in the following chapter.

3 Application of Process Mining for Product Life Cycle Analysis

The basis for the analysis in this paper is a dataset from a make to order business model with high complexity and diversification and is linked to an SAP S4 HANA System. In order to depict the whole process chain there are 202 materials that are at the time of the analysis in the material specific status "End of Life". The timeframe of the analysis is representing three years. This means no further actions in the system should be executed. At first the *data set*, then the used *tool* and finally the process mining *analysis* is described in the following.

Description of the Data Set

The first step is to gather material related information from the ERP System. Within this process, the material creation date and all material master changes are extracted. To conduct drill down analysis, more information among sales, purchase and production orders are selected. Specifically, relevant in that case is the creation date of such. In the next step the dataset is prepared for the process mining software in a .csv file, which will be upload to the process mining software.

Applied Process Mining Tool Celonis

With the execution of the analysis a tool has to be selected. The academic aspect of this research allows to use Celonis as a powerful but flexible tool to execute the rather unusual process mining approach. This tool includes the functionality to upload a modified .csv data file. With the right formatting and uploading sequence the data is converted by the process mining engine into the correct format. This builds the process model, the basis for the following analysis.

Analysis

By conducting process analysis or even optimizing processes, there must be an ideal process flow (target process), that functions as the benchmark. The ideal case for our selected dataset looks as follows and represents the lifecycle of a single material. The lifecycle of the material starts with the creation, followed by a workflow to approve the material. The next step is to set the material in the status of a *prototype*. Once the prototype was successful, the material can be set to *supply chain active*. In this stage, sale orders and subsequent purchase or production orders can be created. Once the material reached the peace in sales the material life cycle enters the *phase out* and lastly the *end of life*. The target process is shown in figure 1.

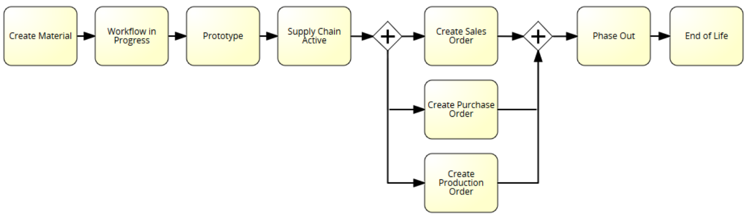

Figure 1: Representation of the company-specific target process

However, process mining technologies reveal the real process flow (as-is process), allow to outline throughput times, find the executed activities and their sequence as well as number of activity executions along the process model. The analysis result reveals the truth behind the process and is shown in figure 2.

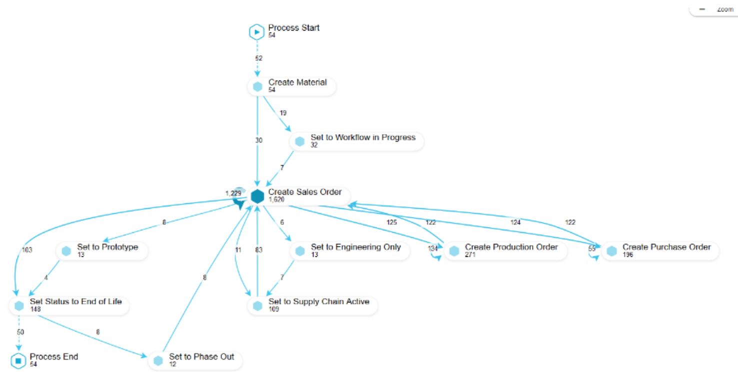

Figure 2: As-is process of the material life cycle

At the example of material lifetime, the first glance of the data shows that this process is not as linear as the target process was described. Materials skip activities, do not follow the path at all, or change the sequence randomly. This picture at the moment does not create value yet. To gain valuable information and derive business decisions, the dataset is needed to be analyzed in detail.

4 Results

The results and focus points are retrieved from typical issues in the day to day business, but do not intend to be exhaustive. In particular, the large amount of data gives seeming endless analysis directions.
The first step in the analysis is to understand the data from a higher level. Viewing the first diagram on the left, the number of materials that followed given paths is represented. In this case only 97 of 202 Materials follow the path of *Set to Workflow in Progress* and *Set to Supply Chain Active*.

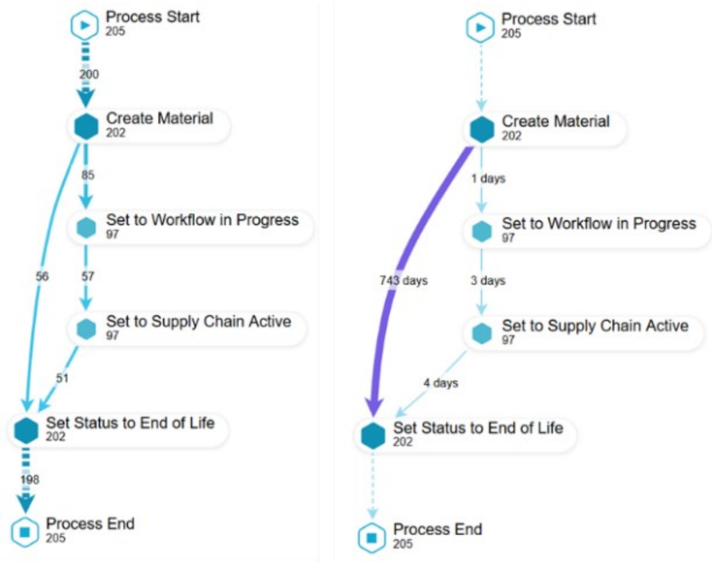

Figure 3: Details of process sequence in throughput time and quantity

One optimization potential might be seen already by switching to the throughput time. To serve the customer as fast as possible, the material

must be set to supply chain active first and the workflow must be finished before a sales order can be create. The throughput time analysis shows already that the workflow execution takes 3 days on median. The variation of this process flow leads to the need for a deeper drilldown.
This view makes the shortcoming of an ideal customer satisfaction more visible. One would be the throughput time overall from the creation of the material to the first sales order creation (41 days median). Others the activities that are executed between those activities, because those drive longer lead times. To show that potential another view that level gives the process flow in the following figure.

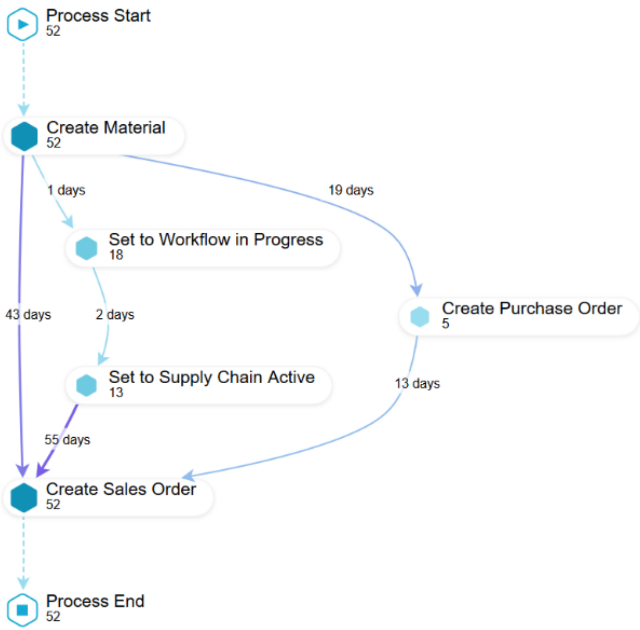

Figure 4: Lead time analysis to serve customers faster

Here several insightful information is hidden, the set workflow activity indeed leads to a longer lead time (18 cases). In 5 cases there is a purchase order created before the sales order was created but this did not affect the throughput time negatively.

Subsequently this information leads to a business research to investigate the real process behind this workflow. Process mining in that case provides the research direction and lists the materials that were affected, but does not give a reason for this.

Focus on Material Status Sequence Violation

The process flow violation in the previous analysis gives an indication that there would be more cases that do not follow the ideal process model.

Another significant process violation to our ideal model is that in 10% of all cases the material status “Prototype” is set after a sales order is created. This has a significant impact on business as the pricing strategy as well as the costing run for the material might not be done yet. The result is a negative impact on the pricing in the future, as the customer might not except price rises in the future anymore.

Focus End of Life

According to the data model the status is set to end of life when there are no further actions taken and the material is not sold or produced in the future. Nevertheless, a process mining based PLM Analysis shows the bare reality.

Those connections to other process steps are found after the status *End of Life* is set:

phase out 3%, set supply chain active 15% and even 4% of materials that have reached their end of life there were sales orders created. To summarize this, more than 20 % of the materials got changed back to another status after it was already set to *End of Life.*

The reason why this can cause concerns for companies is that it keeps the complexity high and drives inventory. For example, if the material reached already the end of life status there should be no material left, the inventory for this product related components should be 0. So whenever there is a sales order created in this status, purchasing must source the components again, possibly to a higher price not in the right quantity or from new vendors. Production must set their machinery up again. In general, the sales of an end of life material cause subsequent non-value adding activities as well as a confusion among departments.

Focus: Changes in a Lifetime

As ERP systems tend to work more autonomously and on a higher level of automation, the number of manual changes is another key performance indicator process mining presents. In the lifetime of 202 Materials, there are 9,880 changes tracked. Hence, this information does not let management perform business decisions. Also in this case a drilldown is needed.

Meaningful are changes of the material description or the purchasing value key, as those count 987 changes and can typically be automated. Modeling this information into quantitative effort and considering each change takes about 3 minutes, the result is that there are about 494 hours spent on changing information in the material master over 3 years of the evaluation timeframe.

Focus: Sales Price Development

With a proper setup of the data model, every change on the material master reveals valuable information. For example, the standard price which is changed over a period of 3 years 515 times and not neglecting this is an essential KPI for the cost tracking. The drilldown to one material reveals even more information. The theory would indicate that product costs and the sales prices go down as the product gets more mature. By applying process mining the reality can be demonstrated in facts and figures: On 156 of 202 materials changes of the standard price are executed. To see if this had a positive or negative impact on business, the development of standard prices is analyzed. The result is that 36 materials show an actual uptrend in costs.

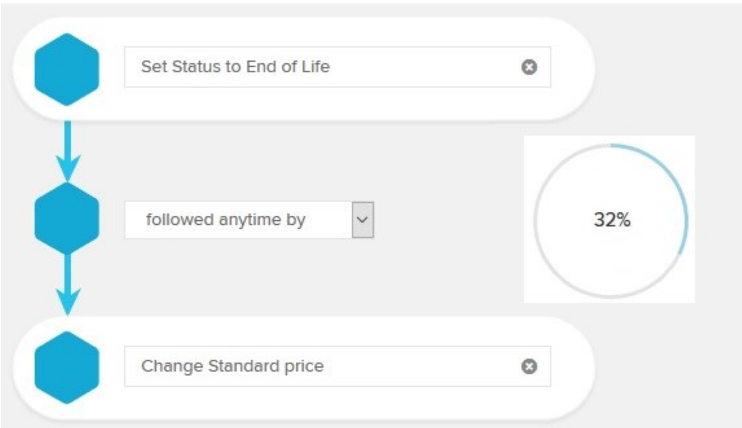

Figure 5: Analysis of process sequence

This information combined with the product life cycle shows that in 32% or on 11 materials those rises were executed after the material status was set to end of life. This supports also the thesis that costs and efforts rise when inactive materials are being touched and foremost used again.

5 Conclusion

The aim of this research was to evaluate if the application of process mining technology in the area of the product life cycle reveals valuable information. When tracing the lifecycle from the creation of the material until it reached the end of life status, using the example of 202 selected materials, the number of activities add up to about 15.000 data points that were executed in the ERP system. The prototypical approach with this real-world data sample shows that process mining technology primarily traces the digital footprints from materials along their lifetime. This reveals facts about the activities that are executed in an ERP System. The resulting product life cycle from the business sample elaborates optimization potential not only in the process flow and the processing time, but also reveals details within process stages. In particular, the development of financial KPIs such as sales price and costs of goods sold has gained attention. Looking at data analytics there might be the claim that other ways to get this information are already established. Nevertheless, the prominent benefit in this analysis is the connection to a timeline. The timeline of a real-world material life cycle provides deeper insights into the development of the KPI. It reveals the details of the changed information, for example the time of the change, whether it was a reoccurring change or a single event as well as the values that were maintained.

However, depending on the business case and the analysis goal, the data model must be adapted and prepared accordingly. In order to apply that to a corporation wide standard, for example, there must be a stable data connection that allows continuous monitoring with real time data. Also, in this extract the scope was limited to selection of materials and a predefined time frame. Further research can be executed by adding more data points. This means other relevant material management systems can be added to gain more data. Besides that, the executed analysis in this paper can be extended and combined with common business use cases including data management.

Using process mining has shown that the technology creates full transparency of the whole material life cycle in an ERP System and allows a wide range of analysis by considering a time series-based development of a material. On the one hand, PLM systems might still be the choice to store and manage product data. On the other hand, when the goal is analyzing the material lifetime stages and the according attributes, process mining is an effective alternative.

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