The Role of Time and Data: Online Conformance Checking in the Manufacturing Domain

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Abstract

Process mining has matured as analysis instrument for process-oriented data in recent years. Manufacturing is a challenging domain that craves for process-oriented technologies to address digitalization challenges. We found that process mining creates high expectations, but its implementation and usage by manufacturing experts such as process supervisors and shopfloor workers remain unclear to a certain extent. Reason 1 is that even though manufacturing allows for well-structured processes, the actual workflow is rarely captured in a process model. Even if a model is available, a software for orchestrating and logging the execution is often missing. Reason 2 refers to the work reality in manufacturing: a process instance is started by a shopfloor worker who then turns to work on other things. Hence continuous monitoring of the process instances does not happen, i.e., process monitoring is merely a secondary task, and the shopfloor worker can only react to problems/errors that have already occurred. 1 and 2 motivate the goals of this study that is driven by Technical Action Research (TAR). Based on the experimental artifact TIDATE—a lightweight process execution and mining framework—it is studied how the correct execution of process instances can be ensured and how a data set suitable for process mining can be generated at runtime in a real-world setting. Secondly, it is investigated whether and how process mining supports domain experts during process monitoring as a secondary task. The findings emphasize the importance of online conformance checking in manufacturing and show how appropriate data sets can be identified and generated.

Keywords: Conformance Checking, Manufacturing Domain, Process Execution Logging, Time and Data, Process Monitoring as Secondary Task, Technical Action Research
1 Introduction

Literature emphasizes the importance of process mining to provide the necessary transparency for pushing digital transformation in manufacturing [11]. A recent Gartner study [8] reports a steep increase in process mining use cases for digital transformation and process automation. A domain that is at the forefront for both use cases is manufacturing. It combines high demands on process transparency and digital transformation and it combines the physical world (e.g., sensors, machines), human work, and manufacturing systems.

Though some use cases for applying process mining in the manufacturing domain have been presented, [11], it remains still unclear how process mining can be actually implemented and used by manufacturing experts (i.e., process supervisors and shopfloor workers), particularly for small and medium size enterprises. The reasons are as follows:

1. Even though the tasks of shopfloor workers are clearly structured and can be viewed as a business process, the operated machines often times lack an actor orchestrating the planned tasks

2. The work reality in manufacturing is that a process instance is started by a shopfloor worker who then turns to work on other things. Hence a continuous monitoring of the process instance does not happen—i.e., process monitoring is merely a secondary task—and the shopfloor worker can only react to problems/errors that have already occurred.

One way to tackle 1 is to have experts create a process model and execute it in their working shifts. Creating a process model reflects an increased work effort by the experts, with no guarantee that, the process model is correctly enacted afterwards without a software that is orchestrating the process. In addition, process mining techniques need a data set to be applied on. Even though many resources create a log for themselves, the logs of the resources need to be collected, linked, and transformed to be suitable for process mining techniques. This is expensive and maximally invasive, because the way how information on the execution of process instances for process mining is stored, is in so called process execution logs (logs for short)\(^1\). On top of that, in order to meet the full spectrum of possible data sources in the manufacturing domain, the collection of process execution data has to be augmented with the collection of sensor and machining data [13].

Automatic process monitoring during runtime constitutes a promising remedy for 2 because in case of deviations or problems, the system could alarm the domain expert instantly. Basically, conformance checking [4] as one of the

\(^1\)In general, a log—usually defined in the XES format ([www.xes-standard.org](http://www.xes-standard.org))—contains information on all process instances that have been executed, i.e., captures the actual behavior of the process. The log consists of so-called traces, where a trace carries the data about a process instance it the executed tasks. Each executed task is stored as an event, usually containing information on the executing resource, a time stamp and a position in the lifecycle of the task.
process mining tasks aims at measuring how well the behavior of a process instances expressed by the corresponding logs fits the behavior described by a process model. Conversely, conformance checking can be used to detect deviations in behavior. Precisely, conformance checking determines alignments between a log and a process model based on moves that reflect matching as well as non-matching behavior. Costs can be assigned to moves for non-matching behavior. Conformance checking based on logs is conducted ex post/offline. However, for supporting process monitoring as secondary task conformance checking must be applied during runtime/online for currently running process instances. Hence, an event stream is used instead of a log.

For the above reasons online conformance checking is considered as suitable analysis technique for monitoring support in manufacturing. Fig. 1 provides an overview what is exactly monitored by the shopfloor worker and the process supervisor. The shopfloor worker monitors the resource behavior based on sensor data and time. Deviations in the sensor data hint to problems with the workpiece quality and occur due to resource degradation [13]. Time-deviations are mostly caused by humans, e.g., someone stepping into the safety area of a machine causing a delay, and hint to problems with work organization. The process supervisor is responsible for monitoring deviations due to ad-hoc adaptations of instances–resolving singular events– or to an evolution of the process model–resolving structural problems. In order to cover all these monitoring tasks, data and time-aware online conformance checking is required, targeting the question of “what is the potential of using various types of data in process mining?”

| Stakeholder          | Observation                                      | Hinting at Problems with... | Root-Cause                      |
|----------------------|--------------------------------------------------|------------------------------|--------------------------------|
| Shop-Floor Worker    | Resource Behavior: Sensor Data Deviation          | Workpiece Quality            | Resource Degredation           |
|                      | Above Threshold                                  |                              |                                |
|                      | Below Threshold                                  |                              |                                |
| Process Supervisor   | Time-Deviation: To Long To Short                  | Work Organisation API        | Safety, Workarounds Software Issues |
|                      |                                                   |                              |                                |
| Deviations of Instance From Model | Many identical One-off Structural Problems | Resource Behaviour |

Figure 1: Time and data-aware conformance deviations and their root-causes in manufacturing

① and ② form the goals of this study. From a methodological point we employ Technical Action Research [15, 16]. "Technical action research (TAR) is the use of an experimental artifact to help a client and to learn about its effects in practice" [16]. Doing so, TAR constitutes the last step “from the conditions of the laboratory to the unprotected conditions of practice”. This study uses the lightweight process execution and mining framework TIDATE as experimental artifact. TIDATE consists of a lightweight and modular process
engine\textsuperscript{2} for modeling and executing the manufacturing processes. Moreover, TIDATE features process logging mechanisms including the linking of sensor and other machining parameters to the logs. Finally, TIDATE features process mining techniques, particularly time and data-aware conformance checking during runtime \cite{13, 12}. TIDATE is applied in a manufacturing environment.

The findings are promising. From the different process mining tasks, process discovery seems to play a minor role in manufacturing whereas the importance of online conformance checking is emphasized. The role of time and data in conformance checking is emphasized, too, i.e., shopfloor workers and process supervisors are actually supported in their process monitoring task. The generation of data sets that are suitable for a product-oriented analysis is possible and does not conflict with the batch-oriented modeling of the processes. Linking sensor data requires a certain upfront effort.

The paper is structured as follows. The methodology and setup of the study is explained in Sec. 2. The implemented approach is then tested and evaluated in Sec. 3. Section 4 answers the knowledge questions of the approach and discusses further improvements. Related work is presented in Sec. 5 and the paper is concluded in Sec. 6 with some finishing thoughts and information on the planned future work.

2 Methodology

This study employs Technical Action Research (TAR) \cite{15, 16} aiming at the validation of an artifact in a realistic case, i.e., the implementation in a real-world organization. This is a major distinction to other forms of Action Research as TAR is technology-driven instead of problem-driven. Section 2.1 outlines the research context of this study, Sect. 2.2 the research design, and Sect. 2.3 the artifact validation.

2.1 Research Context

In TAR, the researcher takes three logically separate roles, i.e.,\ technical researcher, empirical researcher, and helper. Consequently, the researcher in TAR, is allowed to guide domain experts using the artifact, to interfere, and aims to answer research questions with the results of the experiment.

Fig. 2 (based on \cite{15}) shows the three cycles used in TAR that reflect the three roles of the researcher in TAR.

The technical researcher’s design cycle defines the research context of a study. According to \cite{16}, at first, the research problem is investigated and the research context is defined by describing the goals of the created artifact and the current knowledge of the environment. For this study, the experimental artifact is the lightweight process execution and mining framework TIDATE and the practical setting is a manufacturing environment. The clients are the domain experts, i.e., the shopfloor workers and the process supervisors. In this study,\textsuperscript{2}https://cpee.org/
the clients can benefit from time and data-aware conformance checking techniques by detecting errors in the behavior of the manufacturing processes as soon as possible. Moreover, the clients benefit from a minimally invasive generation of product-oriented logs/event streams based on their batch-oriented process models. In the following, we define the research context by dividing the goals into knowledge and improvement goals.

Knowledge goal: Can TIDATE help shopfloor workers and process supervisors in a manufacturing environment in a useful way?

Improvement goals:
- Generate event streams for time and data-aware conformance checking during runtime in a product-oriented manner.
- Highlight time deviations in process instances as soon as possible.
- Highlight data deviations linked to process instances as soon as possible.
- Highlight deviating behavior in the execution order of events in process instances as soon as possible.

Current Knowledge: Process mining techniques have been evaluated using real-world process execution logs. However, these evaluations are usually still based on laboratory settings, i.e., the techniques have not yet been applied in a live real-world setting.

The treatment design yields TIDATE as a lightweight process execution and mining framework to achieve the previously defined goals. For treatment validation TIDATE is validated performing the Empirical cycle of the TAR study. In the protocol for the TAR study the research problem is defined as follows using the checklist from [16].

Conceptual Framework: TIDATE enables the logging of process instance executions and the detection of deviating behavior in the execution.

Knowledge Questions:
How can domain experts easily use process mining techniques?

Can the results provided by process mining techniques be used by domain experts?

Population: The population for this approach consists of companies which already have knowledge of their processes and focus on the correct execution of process instances.

The validation of TIDATE and the answer for the research problem are generated by implementing the treatment at a potential client.

For the client selection process, a suitable client was identified through previous collaborations in different projects. The resources of the client are reachable through web services. Hence only small adaptations of TIDATE were necessary to deploy it at the client’s site. There are threats to generalizability, since the research applied the elaborated approach, but domain experts have been shown the results and developed process models inside the process execution engine to witness the usability of the approach.

2.2 Research Design

After the research context and research problem are defined and a suitable client is found, the empirical cycle is further defined by the researcher, and the helper’s client cycle (cf. Fig. 2) is defined by the researcher and the client. Both cycles interact with each other, therefore the coordination starts as soon as the client is acquired and ends after the client cycle is evaluated (cf. [16]). The problem investigation is the starting point of this design and adaptation of TIDATE to the client’s needs.

Problem Investigation: The client is interested to know how tasks are being executed, and if a process model is available, to know if the execution of instances are matching the behavior of the related model. Common phenomena for this problem are a different execution behavior due to a missing automatic task enactment like a process execution engine and missing data sets allowing the detection of said behavior.

Artifact Design: The artifact TIDATE, that is introduced and implemented at the client, contains a process execution engine. The client models the manufacturing processes which are then enacted and executed by the process execution engine. Moreover, the engine generates an event stream for the executed process instances. This event stream is then used for conformance checking to give the client feedback. Process discovery is not used, since process models have to be created for the use of the process execution engine. The engine then orchestrates the execution of active tasks. Hence, no unknown process models should be discovered from the event stream.

Fig. 3 shows the TIDATE architecture. This architecture can be used as blueprint for (lightweight) process execution and mining frameworks. The process execution engine creates process instances using process models from a repository. The models in the repository are designed by domain experts. The
The conformance checking component is receiving the event stream and the model description from the Logger component and computes the alignment costs every time a new event for a trace is detected. Note that the main focus of this framework is on conformance checking in real time. Since conformance checking of the workflow perspective is a time consuming task to detect the alignment with the smallest cost, the framework focuses on conformance of the data elements. The conformance checking component is receiving data from external sensors as well. The process execution engine typically controls the workflow perspective of a process instance, but the data elements attached to events could still contain wrong information. In addition, not every information affecting the execution of a task is shown in an event. External sources, like the temperature in room for example, can affect an instance, as well. To exploit this information in conformance checking, the data from external sensors can be used, which is typically stored as a time sequence. Time sequences can be compared using, for example, dynamic time warping [13, 10].

2.3 Artifact Validation

To solve the client’s problem of ensuring a correct execution order of the tasks in a process instance and detecting errors as soon as possible, the following data is measured. Domain experts design the process model and together with the researchers create the necessary interfaces for the process execution engine to interact with the machines. After an introduction, the domain experts create
and start the execution of new process instances. The event stream is generated by the process execution engine without needed interference from anyone and the behavior is automatically checked on the data perspective of the events. This data involves time sequences, temporal deviations between events and the duration of events as well as other numerical data relating to the configuration of the participating machines. The conformance costs are reported back to the process execution engine where notification events can be produced to inform domain experts. Domain experts are interviewed in the end to see if process instances that have gone wrong are detected correctly with an increased cost, if the information was useful in detecting the exact problem of the process instance as well if problems occurred during the usage of the framework.

In the following Section 3, the artifact is executed inside the client’s environment, results are generated and possible improvements are being created, based on the feedback of the client.

3 Research Execution

In Sect. 2, the methodology and planned actions for applying and executing TIDATE at a client, i.e., a manufacturing environment, were outlined. This section describes the actual research execution along its setup in Sect. 3.1 and its execution and results in Sect. 3.2.

3.1 Setup

TIDATE as experimental artifact (cf. architecture in Fig. 3) is now implemented at the client. The process execution engine provided by TIDATE, is used at the client, as it already provides a notification stream to detect process model changes as well as the enactment and completion of tasks. For this application, robotic machines and other software interfaces are orchestrated and controlled by the process execution engine.

A client process driving the production of small metal parts called “Turm” by machines for the usage by another company is depicted in Fig. 4. In the beginning the machine’s state is checked and if it is free, the production process is spawned. Note that the whole production process is split into a number of sub processes, so it is easier to read for the domain experts as well as it is easier to maintain small processes. While different parameters are fetched during the “Turn Production” process, the machine is set up accordingly with a program to be deployed on the machine. This allows for a high flexibility to change the process for the machine for each process instance. When the machine is finished, the part is taken out and measured by the Keyence software and afterwards manually by domain experts using MicroVU. In the end it, the produced part is put onto a tray outside of the machine to be used in another process.

The notifications detected by the process execution engine are transformed into an event using the XES format. These events can then be immediately used by the conformance checking algorithms. Additional information which
Figure 4: Process model used in the process execution engine for producing Turm parts.
Figure 5: Small example of process model in execution engine at client. The time $\sim T$ represents the expected task duration on average.

is captured by external sensors is detected by the Fetch task from the “Turm Keyence Measurement” process in Fig. 4. The machine is constantly measuring the diameter of the produced parts, to check if the parts have been correctly produced. The gathered data points of these sensors are aggregated by the software of the machine, fetched by the process execution engine in the Fetch task and then put into the notification of the task execution. Hence a time sequence for the diameter of parts is generated for every process instance. For detecting imperfect parts, the time sequence of a well produced part is saved additionally in the process execution engine which is compared by using dynamic time warping [13].

For the detection of temporal deviations, algorithms from [12] are used. There are 2 types of temporal deviations. The first one is concerning the task duration. If the start and end of a task is supported by the event stream, the task duration can be calculated by determining the difference. The other type of deviation that can occur, is the time distance between the end of a task and the start of the next task. Fig. 5 shows a sub-process as implemented in the process execution engine. For task a3, “Collect Data”, a time duration is put into the model. This duration symbolizes the expected task duration on average. If no time is present, a deviation in this task is seen as harmless. The $z$-score [5] is used to determine the distance of a witnessed task duration to the task duration in the process model. If the distance exceeds a threshold, typically 3, an outlier, hence a severe deviation, is detected.

To apply process mining techniques with correct results, every produced part should be treated like an process instance. An interesting thing emerged at the beginning of the implementation and setup of the framework at the client. Instead of viewing each produced part as a process instance, the shopfloor workers view the production of a batch as one instance. This means, that if out of a batch of 5 for example, only one instance shows deviating behavior, the conformance score is still quite high, since the other 4 instances show no deviations. For the beginning of this study, the produced parts have been divided hard coded, with a better solution presented in Sect. 4.
3.2 Execution and Results

The process execution engine enacts the different tasks for process instances and generates an event stream. How event streams are produced has been discussed in prior work [13]. This work focuses on discussing the results of the experiment after several weeks of testing. The data sets for this analysis can be found here https://tinyurl.com/y6bchfhq/TIDATE/dataset.bise.zip.

Logging: The client is now able to automatically generate an event stream and even process execution logs for the analysis of executed process instances. This allows for repeatable results using process mining techniques, since the process execution log contains time stamps as well to generate an event stream out of it. The logging component is being executed as a separate process, hence it is never interfering directly with the execution of process instances.

Conformance Checking: Interesting results emerged from the first batch of parts produced out of the data set. By taking a look into the process execution logs of the different sub processes, no deviations are detected concerning the event flow of the process instances, but instance b20fed7 of the “IRB2600 Unload to Tray” process, contains time deviations. The “Move up” and “Move down” events, which relate to the tasks a12 and a21 with a task in between “wait” relating to a17. Compared to other process instances and checked with the domain experts, this measurement, done by external sensors, takes about 30 seconds to move a part through the laser. In the log, all 3 tasks are taking 0 seconds. After further investigation, a software error has been detected, leading to no measurement at all by the external sensors, which yielded a return value immediately, hence the task is logged and detected in the event stream as an event, but with an unexpected time stamp and no values attached to the event. Therefore an error, has been detected as soon as possible and the external software with sensors has been restarted to avoid this mistake in future parts.

Another error that has been detected was due to a collision of the robotic machine arm with another machine. This collision led to a slight misplacement of a mandrel of the machine. The mandrel is still within a certain safety range, hence the robotic arm is still reaching inside the machine. However, the produced part is not at the programmed position due to the misplaced mandrel by a few millimeter. Hence the robotic arm is still allowed to move, but grabs the produced part not correctly. The collision is not detectable in the event stream, since the time stamps, data elements, and event order are correct, but the time sequence from the external sensors during the measurement of the current and following parts yields a different time sequence than the expected time sequence which results in a high distance using dynamic time warping. This is detected by TIDATE. After investigating the collision, the reason has been detected. It has been due to a not logged meddling with the program of the robotic arm, which led to an incorrect execution in the process instance.

Other than the situations described above the process instance of the inspected batch conforms to the process model and yields correctly produced and placed parts.

The results of the client’s cycle are discussed in the following Sect. 4 to
conclude the empirical research cycle.

4 Data analysis

TIDATE has been implemented, executed, and evaluated at the client. This section discusses how the previously gathered knowledge questions and improvement goals (cf. Sect. 2.1) can be answered/addressed with the results of the client’s cycle.

Overall, the implementation at the client showed that errors in the process execution can be indeed detected in a real-world setting and help domain experts detect errors quickly.

4.1 Knowledge questions

The first knowledge question targets the ability to use process mining techniques easily in such settings. While the treatment at the client showed that process mining techniques can be applied easily on event streams and process execution logs in a real-world setting, the generation of a sufficient data set needed guidance by researchers. To accomplish the generation of an event stream using a process execution engine, events have to be reported back to the engine. Therefore notifications have to be sent to and from the engine to the services, that are actually performing the tasks. At the client, this has been done using the HTTP protocol and web services. For tasks to be executed by human resources, an automatic way to log the execution of an event is preferable, like in [13].

After setting up a web service that responds to the process execution engine, domain experts by themselves produced the programs to generate the notifications needed to create an event stream. In addition, the domain experts independently created new process models and instances without the need of assistance.

Also for the second knowledge question, if domain experts can actually use the results of process mining techniques, the answer is split into parts. After a process model is created, the process execution engine ensures the correct enactment of tasks for a process instance for that model. Standard conformance checking focuses on the control flow of events, which is a time consuming task and provides results that should be ensured anyway. The client is satisfied with the advantages of creating an executable process model, but is more interested in the data flow of a process instance. Multi perspective conformance checking provides the client and the domain experts with knowledge on process instances going astray through temporal deviations, analyses the behavior and conformance of data elements inside and outside an event stream provided through external sensors. These results are highly appreciated at the client and help domain experts detecting problems in the execution of an automated process early on. At the moment, the results of conformance checking are only published as
alerts. An implementation providing a visualization of deviations is desired as an addition to the framework.

4.2 Improvement goals

For the improvement goals defined in the research context, the implementation and execution at the client yielded promising results. An interesting observation has been made for the generation of suitable data sets. While the process execution engine is generating an event stream and a log for each process instance, the fragmentation of the process “Produce Turm Part” into many sub-processes, resulted into events that are assigned to their individual process instance, but the instance is not related to the production of a specific part. Therefore all spawned sub-processes by the main processes are now related to the main process to allow for better results using offline process mining techniques if desired. Another aspect that we have improved after the client’s cycle, is the separation of produced parts into individual process instances. As explained before, every spawned process is related to the main process in the event stream and log. However, for the interaction with the process execution engine, all production instances of one batch of parts, are designed as one process. This process spawns “Produce Turm Part” as often as parts are wanted, i.e., a loop is spawning the production process 5 times to produce 5 parts during one day. To distinguish between a spawned sub-process and the start of a new main process, we introduced a new icon for BPMN 2.0.

Fig. 6, shows the process for the production for one day. The process utilizes a custom BPMN event (intermediate throwing event, magnifying glass), which allows to group log-data based on individually produced parts, instead of saving it solely based on the given processes structure. While industrial processes are often modeled around the interaction of machines and the production of batches (restricted by raw material availability in the machine), the information derived from online mining is expected to be about individually produced parts. Thus when a process is modeled from a machine coordination point-of-view, a single instance contains information about multiple produced parts. The custom BPMN event is a simple way tell where the event-stream for a single parts, thus allowing to automatically extract and separate part-information.

The highlighting of deviating data elements is already explained in Sect. 3, where the alert of temporal deviations and the increased distance between two time sequences, helped detecting incorrectly executed process instances and discovering the source for the error. So both improvement goals (cf. Sect. 2.1) have been reached. The last improvement goal of highlighting deviating behavior in the execution order, cannot be fully answered at this moment. Since the process execution engine is ensuring the order of the tasks to be fulfilled, the main reason for deviating behavior is an error in the logging component or an attacker tampering with the process execution engine. None of these two scenarios has taken place in the study at the client. While there are studies for online conformance checking, i.e., by [17], using real life data, we could not verify it in our study, because of not occurring. Since conformance checking for
deviating behavior in the order of events is quite time consuming, this result can still show the benefit of having a process execution engine enacting process instances in an organization.

For the research goal, we can conclude that an online process mining framework, indeed supports domain experts in an environment with defined process models. After the implementation, domain experts can model new process models, start and execute process instances. Instances containing errors in the execution are reported to the experts and offer an explanation for incorrect products. The implementation at the client yielded promising results. There are some threats to generalizability, since the manufacturing domain offers process models, which are usually already known by the organization and focuses on conformance checking. Other domains with increased human interactions which do not follow a strict structure could yield incorrect results. Further studies in different domains are required.

5 Related Work

A plethora of process mining techniques has emerged over the last years, dealing with the three areas of process mining: process discovery, conformance checking and, process enhancement [1, 3]. Existing case studies, e.g., [2, 6] apply all three process mining areas to real-world process execution logs, using existing tools such as Disco [7] or ProM [14]. By contrast to this study, these approaches
focus on the applicability of process discovery on real-world logs in an offline manner and the associated filtering of the event log, since without a process execution engine, some noise is expected in the event logs. Conformance checking is evaluated as well, but on the order of events, as well as some social network mining of the resources and various improvements for the process models focusing on the time perspective with process enhancement.

The usage of process mining in organizations and how to start an enterprise with process mining in mind, is explained in [11]. Here several best practices are presented from projects in different organizations, like Siemens, BMW and Uber. The main difference to the TIDATE framework is that the best practice use cases aim at discovering complex process models, which are difficult to understand and design. Therefore the process model is created retrospectively using process discovery on a process execution log. This is due the structure of the organizations and the interaction with other organizations involving human resources. By contrast, in this study, the process models are designed by domain experts to be executed by a process execution engine and the conformance of the process instance is monitored with focus on data and time during runtime.

The work of [9], argues that even though process discovery is commonly present in commercial tools nowadays, the discovered process models are often only visualized in a “directly-follows” graph representation. This simple representation can lead to false conclusions and assumptions about the process model, since it is not clear, where parallel activities or decisions are taking place and what leads to a specific path in the process model. Hence, [9] introduces an extension to “directly-follows” models. Moreover, the approach shows how to apply conformance checking based on the extended models. The approach is evaluated in a real-world setting. In detail, conformance checking is conducted by comparing process models, created by hand, to the generated process execution log. Contrary to the work in this paper, the order of the events is the important aspect when conducting conformance checking, not the focus on data and time.

6 Conclusion

This paper demonstrates how to design and use a process execution and mining framework in manufacturing. In particular, the experimental framework TIDATE has been implemented in a client’s manufacturing environment following a Technical Action Research study.

The implementation at the client

- revealed differences between a real-world setting and the academic environment, in particular, the different perspectives on process instances, i.e., batch-oriented vs. product-oriented.

- led to answers to research and improvement questions, for example, how process mining can be integrated in the manufacturing domain and if domain experts can use these techniques and with how much effort required.
The introduction of a process execution engine and the nature of the manufacturing domain, helped applying process mining and the results look promising. Time deviations and deviations in data elements, even from external sources, like data sensors, are providing much needed information on the conformance of a process instance and give a close inspection to analyze where a process instance is deviating from the expected behavior.

Since not every domain has the same degree of process orientation as the manufacturing domain, conducting a TAR study with TIDATE in another domain is desired. First of all, such a study could shed light on the potential of process discovery and conformance checking on the order of events, since this only played a minor role in this study. Moreover, domains such as health care and logistics seem to have similar demands with respect to time and data-aware conformance checking. In both domains, sensors play an important role and time is a critical factor.

Another important aspect for future work is how the information on deviations is conveyed to the clients, i.e., domain experts. In this study, simple alert notifications are sent if a deviation is detected, but a visualization of the deviating tasks of the process model in the process execution engine, would lower the entry barrier even more for domain experts to get accustomed to process mining.

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