

Temporal Conformance Checking at Runtime based on Time-infused Process Models

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Abstract—Conformance checking quantifies the deviations between a set of traces in a given process log and a set of possible traces defined by a process model. Current approaches mostly focus on added or missing events. Lately, multi-perspective mining has provided means to check for conformance with time and resource constraints encoded as data elements. This paper presents an approach for quantifying temporal deviations in conformance checking based on infusing the input process model with a temporal profile. The temporal profile is calculated based on an associated process log considering task durations and the temporal distance between events. Moreover, a simple semantic annotation on tasks in the process model signifies their importance with respect to time. During runtime, deviations between an event stream and the process model with the temporal profile are quantified through a cost function for temporal deviations. The evaluation of the approach shows that the results for two real-world data sets from the financial and a manufacturing domain hold the promise to improve runtime process monitoring and control capabilities.

Index Terms—Temporal Conformance Checking, Online Conformance Checking, Temporal Profile

I. INTRODUCTION

The current pandemic has put a spotlight on the ability of companies and organizations to react quickly on a radically changed situation. At the same time, business processes have (re-)gained tremendous interest due to their key role in driving digitalization. The consequence is that companies and organizations have to be able to deal with change and evolution in their business processes.

The intended behavior of a business process is described by a *process model*. Based on the model, during runtime, *process instances* are created and executed. Information on the execution of the process instances is stored in so called *process execution logs*, usually defined in the eXtensible Event Stream (XES) format [1]. For each of the process instances, a *trace* is stored, reflecting the sequence of *events* that occurred for the process instance. An event contains information about the executed activities, and an arbitrary number of data elements, i.e., a timestamp or resource. The process execution log hence reflects the actual behavior of the process.

Conformance checking, one of the three main areas of process mining [3], aims at quantifying the conformance between the described and actual behavior of a process [8]. For this, the process model and a process execution log

are analyzed for deviations. If no deviations can be found (“perfect” conformance), a fitness score of 1 is assigned. For any mismatches (i.e., missing events, added events) the fitness score is reduced.

So far, existing approaches have mainly focused on control flow conformance. Multi perspective process mining denotes a research direction that emphasizes the importance of considering other process perspectives such as data, time, and resources for conformance checking, as well [14].

This paper will pick up this line of argumentation and, in addition to control flow conformance, focus on *temporal deviations* in conformance checking. Temporal information in a process can be defined in two different ways: (a) the time between start events of two subsequent tasks (*temporal distance*) and (b) the time between start and end events of a single task (*task duration*) [15]. In general, logs for mining purposes are either generated by extracting data from a specialized information system, or alternatively generated by a process execution engine. Most available data sets only contain end events. Thus temporal distance is the prevalent definition, while some process managements systems produce logs with start and end events and thus allow for the more concise task duration point of view.

Temporal deviations might occur for the following reasons:

- Reduced duration: A task was not executed properly because, e.g., a machine failed or information was missing.
- Increased duration: Preconditions for the tasks have not been met, or hidden dependencies between tasks exist.

This paper aims at finding and quantifying such temporal deviations. By contrast to existing work [14], the temporal information is not available in the form of temporal constraints, but is determined based on an input process execution log. We call the result a *temporal profile*. The input process model is infused with the temporal profile. The goal of this work is to determine temporal deviations of an (ongoing) process event stream with the temporal profile during runtime (online). A *process event stream* contains events reflecting the execution of process instances. Instead of a protocol of finished process instances, the events of all process instances currently being executed are being put into a stream. An event stream contrary to a process execution log is infinite.

Another contribution of this work is to propose a user-adjustable semantic quantification (in the form of an annotation to the process model) in order to quantify the significance of temporal deviations for a certain task. This way, it can be expressed that exceeding the limit of a task duration can be more severe for some events (or tasks) and even affect succeeding events.

Two real-world data sets are used for the evaluation of the approach. The first one is the BPI Challenge 2012, since it meets the criteria of providing the start and end time of at least some events of the process execution log [23]. The other data set is from the manufacturing domain and features the production of industry parts where the whole production process is managed and enacted by a process execution engine.

In Section II, fundamentals on conformance checking are sketched. Section III provides the algorithm for infusing process model with a temporal profile. Moreover, Sec. III introduces the cost function for temporal deviations and the algorithm incorporating it. The contribution is then evaluated and discussed in Sec. IV. Related work in this field is presented in Sec. V Section VI presents conclusions and future work.

II. FUNDAMENTALS

This section provides a brief introduction into conformance checking [3]. Figure 1 shows an abstract example of a process model. Task *A* is followed by task *B*. Either task *C* or *D* can be executed following *B*. After either of *C* or *D* finished, task *E* can be executed.

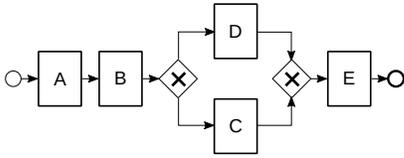


Fig. 1. Process model containing 5 tasks and 1 decision gateway

Conformance checking is one of the three main areas of process mining. It determines if the behavior of a process instance fits the description of a process model. Originally token based replay has been used on a petri net representation of the process model to determine the conformance. Lately, aligning the event sequence of the process instance to the process model is used [2], [4].

Model	A	B	D	E	»
t_3	A	B	»	E	D

TABLE I

ALIGNMENT WITH TWO MOVES DUE TO WRONG ORDER.

Based on the process model in Fig. 1, the following traces can be generated: $t_1 = (A, B, C, E)$ and $t_2 = (A, B, D, E)$. t_1 and t_2 match the process model perfectly. Given a trace $t_3 = (A, B, E, D)$, a deviation can be detected. Event *E* and *D* appear in the wrong order. To align t_3 to the process model, so called asynchronous moves are added to the *alignment*,

depicted with a \gg in the alignment. The alignment necessitates two moves, as can be seen in Tab. I. This is not the only possible alignment for t_3 , as a move in the model and then in the log can be possible as well. To calculate the best alignment for a trace a cost is added for every asynchronous move. Perfectly matching traces yield a cost of 0, while every asynchronous move can increase this value. The cost value for a asynchronous move is defined in a *cost function*. Usually every asynchronous move is assigned a cost value of 1, resulting in an alignment cost of 2 for t_3 . Conformance checking aims to find the alignment with the minimum cost.

III. TEMPORAL CONFORMANCE CHECKING

This section infuses process models with temporal profiles as input for temporal conformance checking using a cost function to quantify temporal deviations.

A. Temporal Profile Generation

The basic idea of temporal conformance checking is to infuse a process model with a temporal profile and then to conduct conformance checking using a cost function that quantifies temporal deviations between the temporal profile and an event stream of interest. The input for temporal conformance checking hence comprises a process model and (i) a process log in an offline setting or (b) an event stream in a runtime (online) setting. For (i) the process log can be split into a training set for calculating the temporal profile and a test set for temporal conformance checking. The evaluation will show both, (i) offline and (ii) online settings.

The temporal profile captures task duration and temporal distance between events/tasks. We will explain both in the following and sketch some scenarios. Algorithm 1 calculates a temporal profile from a process model and a process execution log. An example for a process model infused with a temporal profile is provided in Sec. III-C.

Task Duration: To compare the attached event data between process execution logs in the XES format, standard extensions are available, for example, the name, the timestamp, and the lifecycle of an event. The lifecycle data element of an event reflects its current status. For temporal conformance checking, start and end lifecycle event are needed to calculate the complete task duration by calculating the difference between these two timestamps (cf. Fig. 2 (b)).

Temporal Distance: The temporal distance determines the time after an event is completed and before a new event starts. For this, the events have to contain again a data element describing its lifecycle, i.e., start and complete. We use the notation $|AB|$ for describing the temporal distance between event *A* and *B*. While in a strict sequence of events, like events *A* and *B* in Fig. 2 (a), the computation of the temporal distance is trivial, some interesting occurrences can be witnessed if events are executed in parallel, i.e., event *C* and *D* in Fig. 3.

Event *B* has to be completed before either event *C* or *D* can be started. This leads to 4 possible temporal distances, namely $|BC|$, $|BD|$, $|CD|$, and, $|DC|$. Both, *C* and *D* have to

be finished before event E can be performed, thus the distances $|DE|$ and $|CE|$ emerge as well.

Algorithm 1 calculates the mean and standard deviation for all observed temporal distances and stores them. Infrequent distances can be filtered out using a threshold value.

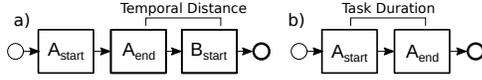


Fig. 2. Temporal Profile – Example.

```

Input:  $M$ : A process model,
 $L$ : A process execution log, containing traces of process instances,  $\kappa$ :
threshold for filtering infrequent time distances
Result:  $M$ : A process model containing information of time distances
1  $td = \text{dict}()$  // Hash Map of Execution time duration
2  $inter\_td = \text{dict}()$  // Hash Map of Inter Time distances
3 for  $trace$  in  $L$  do
4     // iterate over every process instance in the log
5      $current\_starts = \text{dict}()$  // Hash Map for execution time duration
6      $last\_end = \text{None}$ 
7     for  $event$  in  $trace$  do
8         //iterate over every event of trace
9         //  $lc()$  == lifecycle of event,  $ts()$  == timestamp of event
10        if  $event.lc() == 'start'$  then
11             $current\_starts[event.name] = event.ts()$ 
12            if  $last\_end != \text{None}$  then
13                if  $inter\_td[last\_end.name+event.name] == \text{None}$ 
14                    then
15                         $inter\_td[last\_end.name+event.name] = \text{list}()$ 
16                         $inter\_td[last\_end.name+event.name].append($ 
17                             $last\_end.ts()-event.ts())$ 
18                if  $event.lc() == 'complete'$  then
19                    if  $td[event.name] == \text{None}$  then
20                         $td[event.name] = \text{list}()$ 
21                         $td[event.name].append(event.ts()-$ 
22                             $current\_starts[event.name].ts())$ 
23                         $current\_starts.remove(event.name)$ 
24                         $last\_end = event$ 
25         $stats = \text{dict}()$  // Hash Map of all means and standard deviations of
26        time distances
27        for  $key$  in  $td$  do
28             $stats[key] = (\text{mean}(td[key]),\text{stddev}(td[key]))$ 
29        for  $key$  in  $inter\_td$  do
30            if  $\text{len}(inter\_td[key]) \geq \kappa$  then
31                 $stats[key] = (\text{mean}(inter\_td[key]),\text{stddev}(inter\_td[key]))$ 
32         $M.add(stats)$  // Infusing Process Model with Hash Map of time
33        distances
34    return  $M$ 

```

Alg. 1. Temporal Profile Generation

For this, Alg. 1 starts with creating two hash tables [9] to save the time distances, one for task duration and one for temporal distances. Afterwards, each event of every process instance is parsed. If a start event is detected, the temporal distance is calculated to the last detected end event and the timestamp is saved for the task duration. On the other hand, if an end event is detected, the task duration is calculated and the event is saved as the currently last finished event for the temporal distance. Lines 23 and 25 determine the mean and standard deviation and filter out infrequent temporal distances. If no suitable data set is available, domain experts could produce the temporal profile.

B. Temporal Conformance Checking

After temporal profile is calculated, temporal conformance checking can be performed, either online at runtime on an event stream or offline on a process execution log.

The z -score [10] is used to determine the distance of new observations to the gathered data sets from the preparation phase. Since the data for the data sets has been collected in a complete test set, it can therefore be argued that the data set is complete, which enables the use of the z -score. The z -score is defined as follows:

$$z = \left| \frac{x - \mu}{\sigma} \right|$$

Thus, the deviation is calculated by subtracting the mean of all time distances for an event from the new observation and divides it by standard deviation of all time distances for one event. If the z -score exceeds a specified threshold, a deviation is detected. Certain tasks allow a greater deviation while other tasks demand to be very precise. The z -score determines how many standard deviations the observation is distant to the mean. Thus a list of thresholds is used, containing a threshold for every task in the process model to reflect the needs for adjustable outlier detection.

To use this z -score for quantifying the cost of a temporal deviation, a temporal deviation cost is introduced as follows:

The end cost for an alignment calculated by temporal deviation conformance checking is the sum of all costs of structural movements using standard conformance checking, i.e., log and model moves, and of all costs of temporal deviations using the temporal deviation cost function.

Algorithm 2 shows a prototypical implementation for temporal conformance checking at runtime. Line 2 starts a hash table for all currently saved process instances. The parameter $TSIZE$ defines how many process instances can be stored at the same time. Since we are dealing with possibly infinite process instances, only a fixed number can be stored. If the hash table is full, an older process instance is removed from the table. There are many classifiers possible for determining the to be removed process instance. This approach opted for the oldest process instance to be removed, line 19. Lines 7 to 11 create the necessary variables for each instance.

In line 28 the alignment cost for standard conformance checking is calculated [24]. The hash map $unfinished_events$ saves all timestamps of starting events. Every time a starting event is detected, the timestamp is added. If the related end event is detected, line 19, the timestamp is removed from the hash map. For each end event, the temporal deviation cost is calculated based on the duration of the event, line 17. For every detected start event, the temporal deviation cost for inter event time distance is calculated, line 22.

If an event is still being executed and its task duration is already greater than the average time for this task, the temporal deviation cost is calculated using the time duration between the moment the last event is detected in the event stream of this process instance and the starting event, line 26. Instead of event for events in the event stream, the algorithm can be

Definition 1 (Cost Function for Temporal Deviations):

$$\text{temporal_deviation_cost_function}(x, M) = \begin{cases} 0, & \text{if no } \text{mean}(M_x) \text{ available} \parallel \text{z-score}(x) \leq \kappa_{M_x} \\ \omega_{M_x} * \phi * \text{z-score}(x) & \text{otherwise} \end{cases}$$

Let x be a time distance, M a process model containing information of time distances, κ a threshold defined between 0 and ∞ and M_x the data set of related time distances, containing the mean and standard deviation and a related κ -threshold. If a mean is available and the z-score is smaller or equals κ , this function yields 0. Otherwise let ϕ any number between 0 and inf to adjust the impact of a temporal deviation in general and let ω_{M_x} be a weight between 0 and ∞ for the related event to adjust the impact of specific events. The function yields the temporal deviation cost for observations with a z-score greater than the threshold κ .

Input: M : Process Model with information on time distances
 ES : An event stream, sending events related to model M .
 $TSIZE$: Maximum Number of available process instances that can be stored.
 κ_{event} a list of thresholds the maximum allowed z-score per event
 ω_{event} a list of weights for the results of temporal deviation cost function per event
 ϕ : general cost modifier for temporal deviations
Result: C : Cost for last alignment of ES .

```

1 // temporal_deviation_cost_function(x) == tc(x)
2 traces = dict()
3 for e in ES do
4     if e.trace not in traces then
5         if len(traces) ≥ TSIZE then
6             traces.remove_oldest()
7             traces[e.trace] = dict()
8             traces[e.trace]['cost_time'] = 0
9             traces[e.trace]['preceding_event'] = None
10            traces[e.trace]['unfinished_events'] = dict()
11            traces[e.trace]['trace'] = list()
12            t = traces[e.trace]['trace']
13            t.append(e)
14            traces[e.trace]['cost_structural'] =
15                online_conformance_checking(t,e)
16            if e.lc() == 'complete' then
17                if tc(e,M) > κ then
18                    traces[e.trace]['cost_time'] += tc(e,ω_e, φ)
19                    traces[e.trace]['preceding_event'] = e
20                    traces[e.trace]['unfinished_event'].remove(e.name)
21            if e.lc() == 'start' then
22                if traces[e.trace]['preceding_event'] != None and
23                    tc(|traces[e.trace]['preceding_event'][e]|) > κ_e then
24                    traces[e.trace]['cost_time'] +=
25                        tc(|traces[e.trace]['preceding_event'][e]|,ω_e, φ)
26                    traces[e.trace]['unfinished_events'][e.name] = e.ts()
27            for event in traces[e.trace]['unfinished_events'] do
28                if Time.now - M[event].mean() > 0 and tc(event(Time.now-
29                    traces[e.trace]['unfinished_events'][event]),ω_e, φ)
30                    > κ_e then
31                    traces[e.trace]['cost_time'] += tc(event(Time.now-
32                        traces[e.trace]['unfinished_events'][event]),ω_event,
33                        φ)
34            C = traces[e.trace]['cost_structural'] +
35                traces[e.trace]['cost_time']
36            return C

```

Alg. 2. Finding Cost of Alignment

applied periodically as well to update the temporal deviation cost for unfinished events. As can be seen in Alg. 2, the temporal deviation cost is calculated in linear time, leaving calculating the structural conformance checking score, Line , as the only heavy computing task. Splitting the computation of the structural and temporal deviation costs can yield a performance increase and allows for a scalable application of

temporal conformance checking.

C. Illustrating Example

As can be seen in Fig. 3, the process model has been infused with a temporal profile capturing temporal distances and task durations on average and with the standard deviation.

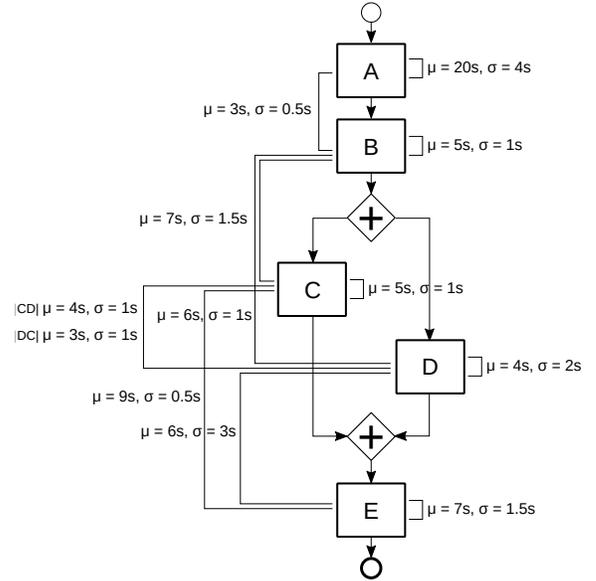


Fig. 3. Process Model Infused with Temporal Profile – Example

Assume the following traces t_1 and t_2 to appear in an event stream of interest:

$$t_1 = ((A_{start}, 0), (A_{end}, 19), (B_{start}, 29))$$

$$t_2 = ((A_{start}, 0), (A_{end}, 20), (B_{start}, 23), (C_{start}, 24), (C_{end}, 28), (B_{end}, 29)).$$

Note that in order to illustrate the run through of Alg. 1 and Alg. 2, the events are listed with their time spent related to the start of the process instance in seconds.

We set ω_{event} for A and B to 1 and for $|AB|$ to 2 to represent a more severe deviation, ϕ to 1 for both instances and κ_{event} to 2 for the task duration of B and to 3 for all other distances. The events in t_1 are in the correct order, so there are no costs for aligning this trace to the process model. The z-score for event A is calculated when A_{end} is detected, which yields 0.25. Since 0.25 is smaller than 3 (κ), no temporal deviation cost is added. When B_{start} is detected, the temporal

deviation cost is calculated based on the temporal distance of 10. This yields a z-score of 14, which is greater than κ , increasing the cost for this trace to 28, since ω is set to 2 for this distance. Assume that 7 seconds passed after B_{start} has been performed and the algorithm has been executed. Since that is greater than the average execution time of 6 seconds of event B , the temporal deviation cost is calculated, which yields a z-score of 2. Because κ is set to 2 for the task duration of B , the cost value is increased by 6. The current cost of this trace is therefore 34.

t_2 shows an deviating structure, since the execution of C has been executed before event B finished, which results in move in the alignment and by using the default conformance checking cost function yields costs of 1. The execution time duration of all events is fitting the process model, as well as the temporal distances. There are no recordings for the temporal distances $|AC|$ and $|CB|$, thus the temporal deviation costs cannot be calculated for these distances.

IV. EVALUATION

Algorithms 1 and 2, together with the cost function for temporal deviations (cf. Def. 1) are evaluated based on two real-world data sets. The one is the BPI Challenge 2012 (BPIC2012 for short) [23], which features a process from the financial domain. This log has been chosen, since it provides lifecycle attributes for at least a few number of events to calculate the temporal distances. The feasibility of the approach is evaluated using this log.

Since no additional knowledge of the log is present to evaluate the results of temporal deviation conformance checking, a second real-world is presented in the evaluation. The second log [12] features a business process in the manufacturing domain¹ and experts are evaluating the results afterwards to assess the applicability of the approach.

A. Financial Example

The data set from the BPI Challenge 2012 contains 262200 events from 13087 process instances. Since only the process execution log is given by this data set, we mainly focus on calculating the additional temporal deviation costs for an alignment without the costs of structural conformance checking and assign ω_x to 1 for every event. The events contain data elements describing the values for a financial transaction as well as timestamps. A mandatory requirement for the elaborated approach of this paper, is the availability of lifecycle attributes of an event.

Out of the 23 different tasks in the business process, only 6 tasks have a lifecycle logged with a start and an end event. This can be explained, because the process consists of 3 inter twined sub-processes, but only sub-process W contains the start and end event of activities, while the other two A and O do not.

We opted for analyzing the data set as a whole instead of breaking it up into 3 different processes, because these

sub-processes are inter-twined, therefore do some temporal distances appear from sub-processes without start events. The task duration does not change if other events happen during the execution. Since no event stream of the data set is available, the data set is split into a process execution log consisting of the first 80% of process instances and an event stream constructed using the other 20% of the process instances, a similar approach to machine learning algorithms [5].

For Algorithm 1, the first 10469 process instances are used as a set to gather the temporal profile.

As can be seen in Tab. II, the task duration varies to a great extent. Often the duration of an event takes seconds, other times the duration spans several days. This can be attributed to the fact, that these events are inter-twined with events from the other sub-processes. Hence the task duration time of these events is depending on the time of the other events. The duration cannot be calculated for the other sub processes, since only end events are found in the process execution log.

As sub-process W contain start events, temporal distances can be determined. We set κ to 20 to filter out distances, that only have been detected like 2% of the time.

The remaining temporal distances can be seen in Tab. III. Again, a wide range of time distances between the events is detected. This is reasonable, because the task durations vary to a great extent as well.

Algorithm 2 is applied to the test set consisting of the remaining traces in the log. Even though the algorithm has been designed for online execution, it is still possible to calculate the temporal deviations in an offline setting. To achieve this all events have been collected and have been sorted according to their timestamp. Each of these events has then been injected into an event stream with random intervals, but still using their original timestamp for the calculation. κ_{event} has been set to 3 for all events, ϕ and all ω_x to 1.

Out of 12650 task duration, 12607 events yielded a z-score below κ , but 43 yield a higher score. The maximum z-score of 3620.9 has been found in process instance 207263. As can be seen in Tab. II, $W_Beoordelen_fraude$ is the event with a small standard deviation. In this process instance the task is started at 09:00 on a Thursday and finished the next day at 06:15. Thus a holiday does not seem plausible and it is likely that something happened during this task. The advantage of using this algorithm online would be the possibility to examine the process instance immediately when enough time has past after the starting event of this task. No process instance showed more than 2 deviations.

Out of 12654 possible temporal distances, 12395 do not deviate and 259 do. The maximum deviations of one process instance is 5, detected in 2 process instances. Without domain experts, it is difficult to classify the severeness of these deviations.

B. Manufacturing Example

The first example showed that the algorithm is returning good results with no knowledge of the underlying process. For

¹http://gruppe.wst.univie.ac.at/data/manufacturing_log.zip

Name	Profile Size	μ	σ	Min	Max
W_Completeren aanvraag	18562	640.03	5883.48	0.77	244731.43
W_Nabellen offertes	18975	560.58	7302.64	0.95	243191.22
W_Valideren aanvraag	6493	1268.71	6098.85	1.1	238256.25
W_Afhandelen leads	4864	1012.62	9905.82	0.67	243739.82
W_Nabellen incomplete dossiers	9574	771.07	8052.62	1.03	239878.67
W_Beoordelen fraude	211	73.77	640.81	0.77	9240.84

TABLE II
BPIC 2012: TASK DURATION IN SECONDS FOR ALL 6 EVENTS OF 3271 PROCESS INSTANCES

Name	Profile Size	μ	σ	Min	Max
A_PREACCEPTEDW_Completeren aanvraag	3819	22875.3	33214.99	3.55	156982.87
W_Completeren aanvraagW_Nabellen offertes	4019	270672.33	308357.9	6.61	1206235.29
W_Nabellen offertesW_Nabellen offertes	14955	258339.44	279374.88	1.4	2572740.11
W_Nabellen offertesW_Valideren aanvraag	2640	233294.08	159396.81	7.2	617152.84
W_Completeren aanvraagW_Completeren aanvraag	12686	79836.59	228186.05	1.47	2583000.9
W_Valideren aanvraagW_Valideren aanvraag	2402	39583.82	112968.6	1.95	1289690.02
A_PARTLYSUBMITTEDW_Afhandelen leads	3905	18670.85	30043.74	11.57	151792.25
W_Afhandelen leadsW_Completeren aanvraag	2064	12132.28	20071.87	6.76	159723.98
W_Valideren aanvraagW_Nabellen incomplete dossiers	1764	5108.96	8359.51	4.62	147659.13
W_Nabellen incomplete dossiersW_Nabellen incomplete dossiers	7809	61731.99	112940.21	1.54	1117225.91
W_Nabellen incomplete dossiersW_Valideren aanvraag	1421	34776.54	75051.87	9.97	614586.68
W_Afhandelen leadsW_Afhandelen leads	942	3669.69	12485.41	1.46	160780.79

TABLE III
BPIC 2012: TEMPORAL DISTANCE IN SECONDS OF THE FIRST 10469 PROCESS INSTANCES WITH κ SET TO 200

the manufacturing data set², a process model with different ω_x and κ_x is provided. An expert has been assessing the results.

Figure 4 shows the manufacturing of a part³. The main process (tasks a1..15) shows the interaction between different machines (EMCO MT45 Turning Machine, ABB IRB2600 Robot, Keyence Optical Measurement Machine) during production, while the sub-process \otimes is spawned for every single produced part, and tracks its full production lifecycle. Every task has an ω assigned, values of 1 signify normal (high) importance. Values of 0 signify that deviations can be ignored. In addition to that, a κ is assigned to each task, representing how many standard deviations an observation can be distant to the mean of a distance. Often 3 is used as a default value to detect outliers [10]. A higher value allows for greater distant distances, while a smaller value implies, that the distance has to be closer to the mean.

The \otimes sub-process is forked, i.e., the main process does not wait for it to finish, but executes in parallel. The duration between the b1 start event and the b1 end event should always be identical to the duration between a8 start event and the a4 end event. For a1 : $\omega = 0$, as a1 forks a sub-process (without waiting for it to end). Hence its duration is negligible.

Every occurrence of $\omega = 1$ is attributed to actual machining of the part, which is expected to show small deviations. When the MT45 turning machine closes its door and starts machining, only two cases can lead to a deviation: A power failure or if raw material or the machining tool breaks. Both of these cases are unlikely. Especially the latter is important. If a tool or the raw material breaks, two things can happen: (1) the machine triggers an emergency stop if any damage due

to flying metal parts is detected, or (2) the machining time is reduced, as there is no longer contact between machining tool and raw material. Thus no friction occurs⁴.

Thus, a first perceived application of temporal conformance checking is to trigger an emergency stop of the machines.

All tasks with the prefix IRB2600 are robot tasks (a10, a11, a12, a13, a14, a15). The robot takes the finished parts out of the MT45 Turning Machine. This can partly happen in parallel to the machining. As soon as the robot leaves the confines of the MT45, the machine can start producing the next part. While the MT45 is producing the next part, the robot (a12, b2) scans the part with the help of a Optical Measurement Machine, and (a15) puts it on a tray which, in turn, is placed on pallet with 50 other trays. All of the IRB2600 tasks are expected to show small deviations, except for a15. As all the trays are on a different position on the pallet, each operation should have a slightly different duration, thus yielding the highest standard deviation of all tasks. All robot tasks are also prone to extreme outliers, as the robot is subject to an industrial safety mechanisms: whenever someone accidentally walks close to the robot, a full emergency stop is triggered to avoid injuries. This can indeed be observed in the data multiple times. Afterwards it is not always trivial to restart the robot as sometimes it has to manually be moved into a defined state, before the process can be continued.

As a second application, temporal conformance checking can be used to automatically determine the significance of cases, in order to notify personnel for solving the situation.

Table IV shows selected durations of different tasks. Temporal conformance checking proves efficient in pointing out small deviations in the manufacturing process, instantaneously at runtime. For the task duration, 27 deviations of 1373 distances

²http://gruppe.wst.univie.ac.at/data/manufacturing_log.zip

³Note that the tasks IDs a1 to a15, and b1 to b4, are neither continuous nor in sequence as this version of the process is the result of several redesigns

⁴This can also be confirmed through lower power usage.

Name	Profile Size	μ	σ	Min	Max
IRB2600 Grip	30	40.66	6.3	37.32	74.03
IRB2600 Extract	30	23.17	1.43	21.21	28.85
IRB2600 Portal to Door	30	12.22	6.28	9.48	45.91
IRB2600 Door to GS	30	12.47	0.56	11.48	13.85
IRB2600 GS to Take	30	14.78	0.47	13.96	15.81
IRB2600 Take to GS	30	10.5	1.1	9.69	15.73
IRB2600 GS to Door	30	11.49	0.7	10.1	13.12
IRB2600 Door to Scanner	30	13.75	1.62	11.19	18.2
IRB2600 Scan	30	29.59	1.82	26.08	32.59
IRB2600 Scanner to Door	30	12.89	0.98	11.19	14.84
IRB2600 Door to Portal	30	10.96	1.47	9.56	18.03
IRB2600 Unload to Tray	30	20.86	9.6	17.4	69.16

TABLE IV
MANUFACTURING: TASK DURATION IN SECONDS OF FIRST 30 PROCESS INSTANCES IN THE DATA SET.

like resource and time. In their approach conformance is checked based on constraints for the data elements contrary to a previously mined temporal profile.

Temporal anomaly detection [18], aims at finding deviations in the execution time duration using a Bayesian model as well as distinguishing between temporal deviations and measurement errors. Contrary to our approach, outliers are only pointed out, but not quantified in term of fitness costs.

VI. CONCLUSION

This paper introduces temporal conformance checking in order to detect and quantify temporal deviations for task durations and temporal distances between events. The approach can be executed in an offline and online setting. For an offline setting, a process execution log can be split in training and test sets. Based on the training set and the process model, a temporal profile is calculated. In addition, the tasks in the process model can be annotated with their significance for temporal conformance. The temporal profile and the model can then be compared to the test set (offline) or an even stream of interest (online).

The evaluation is conducted with two real-world data sets. The data set from the financial domain demonstrated the feasibility of the approach for an offline setting and without expert knowledge. The data set from the manufacturing domain showed the applicability of the approach in an online setting. Moreover, as the results could be checked with an expert, two applications for the proposed temporal conformance checking were identified, i.e., triggering emergency machine stops and based on the significance of the deviations notifying personnel.

A drawback of this approach is the requirement of lifecycles attached to events, in order to distinguish start and end events. Without this, the distance within events cannot be detected at all and the distance between events can only be guessed.

For future work, we plan an online visualization which aims at making temporal deviations easily detectable by experts. A more in-depth analysis on time distances for parallel tasks is planned as well as dynamically calculating weights assigned to a task, to better reflect the impact of certain deviations.

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REFERENCES

- [1] IEEE standard for extensible event stream (XES) for achieving interoperability in event logs and event streams. IEEE Std 1849-2016 pp. 1–50 (Nov 2016)
- [2] Van der Aalst, W., Adriansyah, A., van Dongen, B.: *Replaying history on process models for conformance checking and performance analysis*. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 2(2), 182–192 (2012)
- [3] van der Aalst, W.M.P.: *Process Mining - Data Science in Action*, Second Edition. Springer (2016)
- [4] Adriansyah, A.: *Aligning observed and modeled behavior*. Ph.D. thesis, Department of Mathematics and Computer Science (2014)
- [5] Alpaydin, E.: *Introduction to machine learning*. MIT press (2020)
- [6] Berndt, D.J., Clifford, J.: Using dynamic time warping to find patterns in time series. In: *KDD workshop*. vol. 10, pp. 359–370. Seattle, WA (1994)
- [7] Burattin, A., Sperduti, A., van der Aalst, W.M.: Control-flow discovery from event streams. In: *2014 IEEE Congress on Evolutionary Computation (CEC)*. pp. 2420–2427. IEEE (2014)
- [8] Carmona, J., van Dongen, B.F., Solti, A., Weidlich, M.: *Conformance Checking - Relating Processes and Models*. Springer (2018), <https://doi.org/10.1007/978-3-319-99414-7>
- [9] Cormen, T.H., Leiserson, C.E., Rivest, R.L., Stein, C.: *Introduction to algorithms*. MIT press (2009)
- [10] Crocker, L., Algina, J.: *Introduction to classical and modern test theory*. ERIC (1986)
- [11] Eder, J., Panagos, E.: *Managing time in workflow systems*. na (2001)
- [12] Florian Stertz, Stefanie Rinderle-Ma, J.M.: Data set containing process execution log data with time sequence information for conference proceeding 2020 paper: Analyzing process concept drifts based on sensor event streams during runtime. <http://dx.doi.org/10.6084/m9.figshare.12472634>
- [13] Leemans, S.J., Syring, A.F., van der Aalst, W.M.: Earth movers stochastic conformance checking. In: *International Conference on Business Process Management*. pp. 127–143. Springer (2019)
- [14] Mannhardt, F., de Leoni, M., Reijers, H.A., van der Aalst, W.M.P.: Balanced multi-perspective checking of process conformance. *Computing* 98(4), 407–437 (2016)
- [15] Posenato, R., Lanz, A., Combi, C., Reichert, M.: Managing time-awareness in modularized processes. *Software and Systems Modeling* 18(2), 1135–1154 (2019)
- [16] Richter, F., Seidl, T.: Tesseract: time-drifts in event streams using series of evolving rolling averages of completion times. In: *International Conference on Business Process Management*. pp. 289–305. Springer (2017)
- [17] Rodriguez-Fernandez, V., Trzcionkowska, A., Gonzalez-Pardo, A., Brzywczy, E., Nalepa, G.J., Camacho, D.: Conformance checking for time series-aware processes. *IEEE Transactions on Industrial Informatics* pp. 1–1 (2020)

- [18] Rogge-Solti, A., Kasneci, G.: Temporal anomaly detection in business processes. In: International Conference on Business Process Management. pp. 234–249. Springer (2014)
- [19] Rozinat, A., Van der Aalst, W.M.: Conformance checking of processes based on monitoring real behavior. *Inf. Syst.* 33(1), 64–95 (2008)
- [20] Sani, M.F., van Zelst, S.J., van der Aalst, W.M.: Conformance checking approximation using subset selection and edit distance. In: International Conference on Advanced Information Systems Engineering. pp. 234–251. Springer (2020)
- [21] Senderovich, A., Weidlich, M., Gal, A.: Temporal network representation of event logs for improved performance modelling in business processes. In: International Conference on Business Process Management. pp. 3–21. Springer (2017)
- [22] Stertz, F., Rinderle-Ma, S., Mangler, J.: Analyzing process concept drifts based on sensor event streams during runtime. In: to appear in Business Process Management, 18th International Conference, BPM 2020. Springer International Publishing (2020)
- [23] Van Dongen, B.F. (Boudewijn): Bpi challenge 2012 (2012), <https://data.4tu.nl/repository/uuid:3926db30-f712-4394-aebc-75976070e91f>
- [24] van Zelst, S.J., Bolt, A., Hassani, M., van Dongen, B.F., van der Aalst, W.M.: Online conformance checking: relating event streams to process models using prefix-alignments. *Data Science and Analytics* pp. 1–16 (2017)