Conformance Testing: Measuring the Alignment Between Event Logs and Process Models

A. Rozinat and W.M.P. van der Aalst

Department of Technology Management, Eindhoven University of Technology
P.O. Box 513, NL-5600 MB, Eindhoven, The Netherlands.

{a.rozinat,w.m.p.v.d.aalst}@tm.tue.nl

Abstract. Many companies have adopted Process Aware Information Systems (PAIS) for supporting their business processes in some form. On the one hand these systems typically log events (e.g., in transaction logs or audit trails) related to the actual business process executions. On the other hand explicit process models describing how the business process should (or is expected to) be executed are frequently available. Together with the data recorded in the log, this raises the interesting question "Do the model and the log *conform* to each other?". Conformance testing, also referred to as conformance analysis, aims at the detection of inconsistencies between a process model and its corresponding execution log, and their quantification by the formation of metrics. This paper proposes an incremental approach to check the conformance of a process model and an event log. At first, the *fitness* between the log and the model is ensured (i.e., "Does the observed process comply with the control flow specified by the process model?"). At second, the *appropriateness* of the model can be analyzed with respect to the log (i.e., "Does the model describe the observed process in a suitable way?"). Furthermore, this suitability must be evaluated from both a *structural* and a *behavioral* perspective. To verify the presented ideas a *Conformance Checker* has been implemented within the ProM framework.

Contents

1 Introduction

It has not been a long time that companies have got software tools in their hands to support their operational business processes. The maturation of other technologies such as database systems and computer networks enabled automated support for both the execution of steps within a business process (e.g., invoking a web service) and the handling of a business process as a whole. Business Process Technology (BPT) is a term subsuming all the techniques dealing with the computer-aided design, enactment and monitoring of business processes. Process Aware Information Systems (PAIS) denote the many systems dealing with business processes in some form; either explicitly such as in Workflow Management (WFM), but also includes systems that have a wider scope such as Enterprise Resource Planning (ERP) or Customer Relationship Management (CRM) systems. Many companies have adopted some of these PAIS and after their installation they are now interested in optimizing the underlying processes. Business Activity Monitoring (BAM) and Business Process Redesign, or Reengineering, (BPR) are current buzzwords accounting for that.

Process mining techniques provide a powerful means to analyze existing business processes on the basis of the actual execution logs. These execution logs can be extracted from almost every PAIS [6] and contain events referring to certain business activities that have been carried out; for this reason they are also called *event logs*. Based on the event log a *process model* can be derived, reflecting the observed behavior and therefore providing insight in what actually happened. In contrast, it is very often the case that there is already a model available, defining how the process should be carried out. Together with the data recorded in the log, this raises the interesting question "Do the model and the log *conform* to each other?".

This question is highly relevant as the lack of alignment may indicate a variety of problems. On the one hand it might reveal that the real business process is not carried out in the way it should be, and therefore may trigger actions to enforce the specified behavior. On the other hand the process model might be either outdated or just not tailored to the needs of the employees actually performing the tasks, such that highlighting this issue facilitates the redesign of the model and therefore increases transparency. But even if the model and the log *do* conform to each other, this can be an important insight as it increases the confidence in the existing process model and may found further analyses based on this model, accounting for the validity of their results with respect to the real business process [12].

Conformance testing, or conformance analysis, aims at the detection of inconsistencies between a process model and and its corresponding execution log, and the quantification of the gap. To make this operational one needs to define metrics. In doing so it constitutes an effective instrument for a business analyst who—based on the insights gained—may motivate suitable alignment activities, be it with respect to the model or the actual business process.

In the scope of this paper conformance testing is approached from a control flow perspective, using Petri nets [15] for the representation of process models. The findings are generally applicable. However, the metrics are tailored towards Petri nets and would need to be adapted to other

process modeling languages. Independent of the form of representation there are two dimensions of conformance. The first dimension is *fitness*, which can be characterized by the question "Does the observed process comply with the control flow specified by the process model?". The second is *appropriateness*, which can be associated with the question "Does the model describe the observed process in a suitable way?". Furthermore, this suitability must be evaluated from both a *structural* and a *behavioral* perspective.

To verify the presented ideas a *Conformance Checker*[1] has been implemented as a plug-in for the ProM framework.

In the remainder, at first, the pursued approaches are positioned in more detail, and some preliminaries in the context of conformance testing are considered in Section 2. Then, the actual conformance metrics are defined in Section 3, with the help of a running example. Afterwards, the implementation work is documented in Section 4. Finally, related work is described in Section 5 and the paper is concluded in Section 6.

[1]The Conformance Checker and the files belonging to the example models and logs used in this paper can be downloaded together with the Process Mining (ProM) framework from *http://www.processmining.org*.

2 Preliminary Considerations

To clarify the setting in which conformance testing can be of interest, one needs to reflect on how these discrepancies between a process model and its execution log may emerge at all. Firstly, a process model can be used in a *descriptive* manner, i.e., it rather serves as a template for implementing the process, or even only constitutes an informal model for a process not being directly supported by something like a WFM system. Secondly, it can be used in a *prescriptive* way, i.e., the model "becomes" the process, e.g., by being enacted by a process engine. Clearly the former type is of interest as inconsistencies may easily occur between the model and the process actually carried out. But also the latter can be subject to the application of conformance analysis techniques as, on the one hand, there is always the issue of process evolution [12], and on the other, even more important, there is no effective means of forcing a human to do something [13, 12, 1]. BPT is typically used to support a given human-centered system, guiding cooperative work of human agents while automatically invoking some computerized tools. Therefore, deviations are natural and the current trend to develop systems allowing for more flexibility (cf. Case Handling systems like Flower [9]) accounts for this need.

So the question is not in the first place whether deviations from the process as intended are possible (since they are expected as soon as humans are involved), but rather whether all the information necessary can be collected to analyze these definitions (e.g., if people work behind the back of a too restrictive system this might be not visible in the execution log).

In general, the events contained in a process execution log may have various kinds of data attached to it, such as the name of the resource performing the task, or a time stamp. In the scope of this paper, however, only the control flow perspective is considered and therefore the events in the log are expected to (i) refer to an activity from the business process, (ii) refer to a case, and (iii) be totally ordered. The first condition is a more general requirement and means that the events must have something to do with the observed business process. However, not every event must directly refer to a task in the given process model, a more in-depth evaluation of the various mapping possibilities and how they are handled is provided in Section 2.3. The second requirement assumes that the recorded steps can be associated with a process instance, i.e., that different executions of the process are distinguishable from each other. The third requirement stems from the fact that control flow is about the causal dependencies among the steps in a business process, i.e., it specifies in which order they can be executed.

As already stated, the process model will be represented in the form of a Petri net, which, due to its formal semantics, enables a precise discussion of conformance properties. More work is required to directly apply the defined metrics to other modeling languages. However, as a first step it is also conceivable to make use of, or customize, existing conversion methods. For example, Event-driven Process Chains (EPCs), as used in the context of SAP R/3 [24] and ARIS [32], may be mapped onto Petri nets as it has been shown in [17]. What is more, it makes sense to assume some notion of *correctness* with respect to the model. Otherwise one could not de-

termine whether, e.g., a failure in following a given log trace in the model indeed indicates a conformance problem or whether the model itself was not properly designed (and therefore does not allow for correct execution anyway). But this is mainly an issue of interpretation, and in principle it is possible to also detect a correctness problem by the means of conformance testing. Since here Petri nets are applied in the context of business processes, it is reasonable to consider a well-investigated subclass of Petri nets for this purpose, which is the class of *sound WF-nets* [2]. A WF-net requires the Petri net to have (i) a single *Start* place, (ii) a single *End* place, and (iii) every node must be on some path from *Start* to *End*, i.e., the process is expected to define a dedicated begin and end point and there should be no "dangling" tasks in between. The soundness property further requires that (iv) each task can be potentially executed (i.e., there are no dead tasks), and (v) that the process—with only a single token in the *Start* place—can always terminate properly (i.e., finish with only a single token in the *End* place). Note that the soundness property guarantees the absence of deadlocks and live-locks.

In fact, there is another root cause for inconsistencies between a given process model and its corresponding execution log, which has not been mentioned yet. It is the issue of (technically) erroneous insertions or non-insertions of events, or mistakes in ordering them, while recording the event log, which is called *noise*. In general, noise cannot be distinguished from inconsistencies stemming from real process deviations and therefore in the remainder it is abstracted from. But if one could somehow separate the noise from other deviations, e.g., knew for some completely automated process that there were only logging failures (i.e., noise) possible, then one could measure the degree of noise in the log with the help of conformance testing techniques.

Figure 2.1 shows that there are different levels that may represent the behavior of a business process. At the top one can see the process model, marked as reference model, which is given as a Petri net graph. At the bottom the event log is given as a set of event sequences corresponding to real executions of the business process.

Different ways are conceivable to measure, e.g., the quantitative correspondence between such an event log and the process model. A rather naive approach would be to generate all firing sequences allowed by the model and then to compare them to the log traces, e.g., using string distance metrics [26]. Unfortunately the number of firing sequences increases very fast if a model contains parallelism and might even be infinite if one allows for loops. Therefore, this is of limited applicability. Another approach is to replay the log in the model while somehow measuring the mismatch, which will be described in Section 3.3 in more detail. A notable advantage of this *log replay analysis* compared to the possibility to apply *process mining* techniques [7, 6] for deducing a mined process model (e.g., also as a Petri net) and to subsequently compare it to the given reference model on the graph level, which is called *delta analysis* [1], is that for carrying out the log replay the log does not need to be *complete*, i.e., contain sufficient information to derive conclusions about the underlying behavior.

In order to bridge the gap between the event stream level of the log and the graph level of the process model one can also use intermediate representations. As an example, the *multi-phase process mining* technique [16] makes use of an intermediate representation called instance graphs, also known as partially ordered runs, which can be derived from the log. They contain only concurrent behavior but no alternatives and, e.g., can be converted to instance EPCs (i-

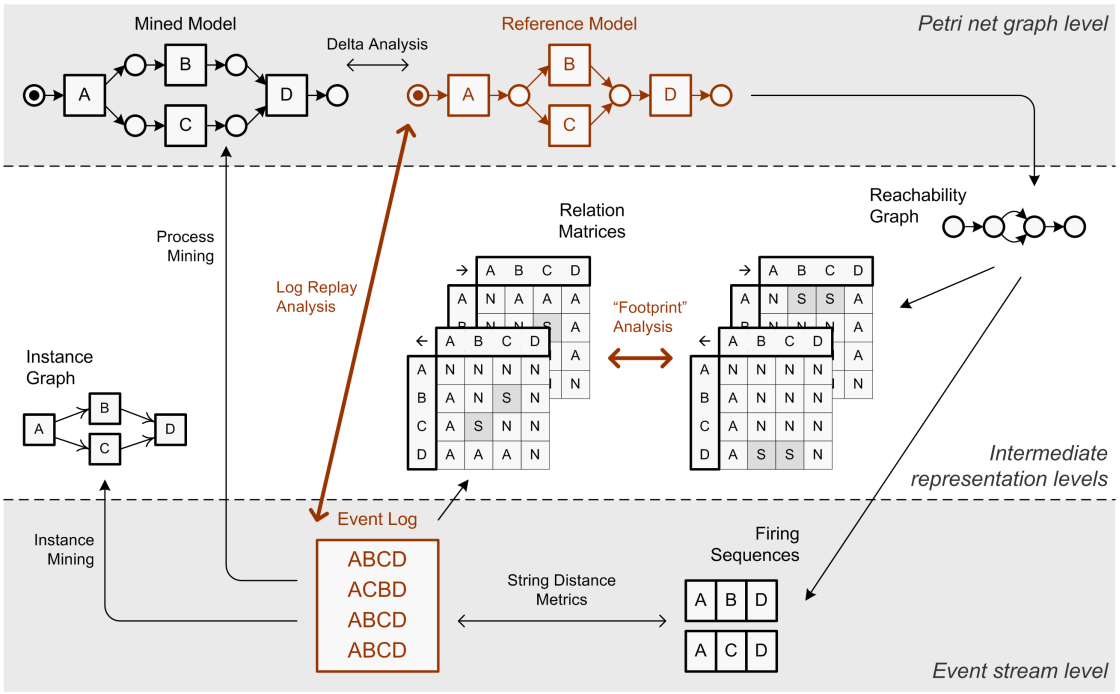


Figure 2.1: Conformance analysis involves different representation levels

EPCs), which in turn can be imported into ARIS PPM (Process Performance Monitor) [22] for further analysis or aggregation into a complete process model in terms of an EPC. Similarly, the approach in Section 3.6.2 will make use of an intermediate representation in form of relation matrices, which are derived from both the process model and the event log, and subsequently can be be compared with each other.

In the remainder of this section the issue of measurement is considered first in Section 2.1. Then, the variety of interpretation possibilities in the context of conformance testing is illustrated in Section 2.2, and finally the handling of the mapping between modeled tasks and log events for the presented approaches is clarified in Section 2.3.

2.1 Measurement in the Context of Conformance Testing

Measurement can be defined as a set of rules to assign values to a real-world property, i.e., observations are mapped onto a numerical scale. These numerical values can then either be interpreted directly (such as measuring temperature) or they can be further processed, e.g., combined with other *measures*, to gain insight into a more complicated matter. Among many other application fields measurement is also used in the Software Engineering domain to, e.g., determine the degree of completed work packages for tracking the progress of a project, or to measure the complexity of a software product [18].

The term *metric* originates from the field of mathematics and denotes a function that determines the distance of two points in a topological space. Hence strictly speaking, it is not correct to call the measurement of a certain property of, e.g., a software system a metric, which would rather be imposed by comparing—and determining the difference of—two software systems. But as in technical environments the implicit intention of measurement is usually to interpret the result with respect to either a past state, or a certain desirable or undesirable state, it is common to call a system or standard of measurement a metric [27].

The example of measuring the complexity of a software product already indicates that it is not always easy to approach a property by measurement. At the first glance it seems impossible to capture such an abstract concept as complexity by measurement, and though there are dozens of measures or metrics defined for it [35]. The conformance of a process model and an event log is not easy to quantify as well; the intuitive notion of conformance is difficult to capture in a metric. This is caused by the fact that the comparison of a process model and an event log always allows for different interpretations (see Section 2.2) and makes it difficult to carry out a scale type discussion with respect to the metrics defined.

Facing so much uncertainty it is wise to impose some requirements to ensure the usefulness of a measure. Based on [27] the following requirements are considered relevant and will be linked to conformance testing. Furthermore, an additional requirement called *localizability* has been identified and included in the list.

Requirement 1 (Validity) *Validity means that the measure and the property to measure must be sufficiently correlated with each other.*

This is a very obvious requirement, which means that, e.g., an increase in conformance should be reflected by some increase of the measured conformance value. Usually, this requirement is already met by the motivation of the formation of a metric.

Requirement 2 (Stability) *Stability means that the measure should be stable against manipulations of minor significance, i.e., be as little as possible affected by properties that are* not *measured.*

In the context of conformance testing a violation of the stability requirement could, e.g., be given for a metric that is affected by the position of a conformance problem (i.e., that yields a different value for a mismatch located close to the start of a trace compared to one close to the end). This is a very important requirement as an unstable metric might result in two measured values not being comparable with each other.

Requirement 3 (Analyzability) *Analyzability, in general, relates to the properties of the measured values (e.g., whether they can be statistically evaluated). In the remainder, the emphasis is on the requirement that the measured values should be distributed between* 0 *and* 1*, with* 1 *being the best and* 0 *being the worst value.*

For conformance testing it is in particular important that a metric always yields an optimal value (i.e., 1) in the case there is no conformance problem of that particular type. This extends the usefulness of the metric beyond a merely comparative means towards being an indicator, i.e., indicating whether there is an issue to deal with or not.

Requirement 4 (Reproducibility) *Reproducibility means that the measure should be independent of subjective influence, i.e., it requires a precise definition of its formation.*

Reproducibility is a general requirement calling for a measure being as objective as possible, so that, e.g., different people may arrive at comparable results. This holds also for conformance metrics.

Requirement 5 (Localizability) *Localizability means that the system of measurement forming the metric should be able to locate those parts in the analyzed object that lack certain desirable (i.e., the measured) properties.*

It is very important that a conformance problem is not only reflected by the measured value but can also be located, e.g., in the given process model. This is crucial for the business analyst as she needs to identify potential points of improvement.

This paper follows the common practice in using the term metric and tries to meet the listed requirements when defining a metric.

2.2 Interpretation Perspectives

When analyzing discrepancies between two objects it is natural to ask for the cause of the mismatch, if any. For this it is important to keep in mind that every interpretation is (implicitly) based on a certain point of view. As an example imagine two strings being compared with each other, one missing element in one of them could always be interpreted as an extra element within the other. Likewise, this holds for comparing a process model with a set of log traces. Figure 2.2 shows a single log trace *AC* and a process model allowing only for the execution of the sequence *ABC*, which cannot be directly matched with each other. Depending on the interpretation perspective two different conclusions may be derived, namely:

1) either the log trace is assumed to be correct and consequently the task *B* is superfluous in the model and should be removed,

2) or the model is assumed to be correct and therefore the log event *B* is considered missing in the log, i.e., *B* should have been executed.

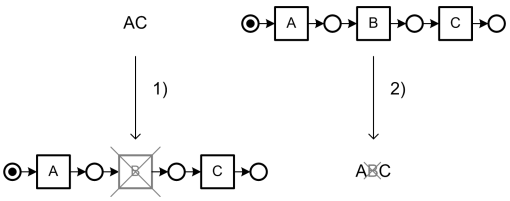


Figure 2.2: Different conclusions based on a different point of view

In general the two perspectives are equivalent and their validity depends on the different circumstances in which conformance testing might take place. However, it is important to be conscious of the current view point and its potential implications.

But even if one perspective is fixed, different interpretations regarding the type of error may arise. For example, an approach to experiment with noise (i.e., erroneously logged or non-logged events) is to *remove* and *swap* elements of a log trace [28]. The swapping corresponds to the correct recording but wrong ordering of the logged events. If one considers removal and swapping each as an equally severe root cause for noise, then the application of some conformance metric evaluating the string distance [26] between the noisy log trace and the correct model path is not valid for measuring the percentage of noise in the log. The reason for this is that swapping results in a greater string distance than the removal of one single event as it affects two events (i.e., one needs one insert and one remove operation to compensate the effect).

Since conformance analysis involves a process model representing not one but several potential execution sequences, even more different conclusions could be derived. As an example consider Figure 2.3, which is an extension of the example in Figure 2.2. Although it keeps the log-based perspective, i.e., the log is considered to be correct, there are multiple interpretations possible, namely:

1a) either task *B* is considered superfluous and the model is adjusted by removing it,

1b/c) or one might want to extend the behavior of the model by adding either the possibility to skip task *B* or an alternative path only executing *C* instead of *BC*.

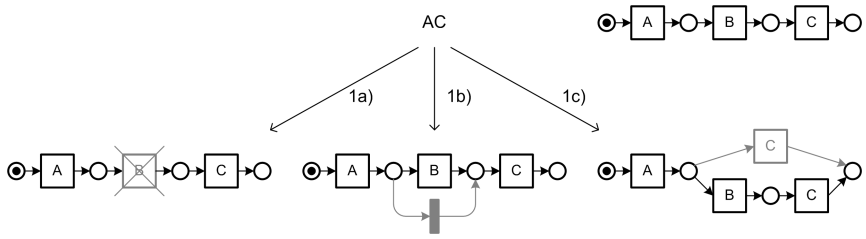


Figure 2.3: Different interpretations based on the same log-based perspective

Another example in Figure 2.4 shows that although sticking to the model-based perspective, i.e., the model is considered to be correct, multiple corrective actions are conceivable as well, namely:

2a) either log event *B* is missing, i.e., *B* should have been executed,

2b) or log event *C* is missing, i.e., *C* should have been executed.

These simple, schematic examples illustrate that a root cause analysis for a mismatch between process model and event log will always lead to a variety of possible interpretations. When applying conformance analysis techniques to a real business process this can be solved with the help of domain knowledge.

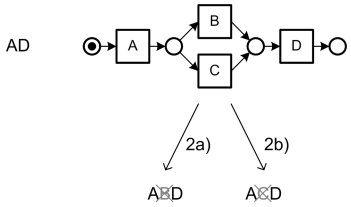


Figure 2.4: Different interpretations based on the same model-based perspective

2.3 Mapping Model Tasks onto Log Events

An essential preparatory step for performing any kind of conformance analysis is associating the tasks in the process model with events in the log file. For this purpose one must abstract from the concrete occurrence of a log event (also called audit trail entry), which, assuming a totally ordered log, has a unique position and might carry additional data like, e.g., a time stamp, an originator etc.; to determine log event *types*. All log events stemming from the same kind of action then share the same log event type, which can be thought of as a common label. Therefore, stating that "log event *A* happened" strictly speaking means that "an instance of log event type *A* has occurred".

Naturally, both the availability of domain knowledge (i.e., understanding the business process) and proficiency with respect to the enactment technology used (i.e., understanding the log format) is required to establish the mapping for a real business scenario. On a logical level, however, the following types of mapping between a *set of tasks in a model* and a *set of log event types* observed in a log can be identified.

1-to-1 mapping Each task is associated with exactly one type of log event (i.e., a function) and no other task in the model is associated with the same type of log event (i.e., an injective function). Furthermore, all log events are associated with a modeled task (i.e., a bijective function). Although activities in real business scenarios take time (i.e., have a start and an end), it is useful to assume one single event (typically this corresponds to a *complete*[1] event) being present for the execution of a task as the minimal information being logged to keep the approach as universal as possible.

In the remainder of this paper the label of a task corresponds to the label of its associated log event type.

1-to-0 mapping A task in the model is not logged and thus is not visible in the log, which is referred to as *invisible task*. An example for such a task not having a correspondent in the log could be a phone call, which is included as a step in the process definition but not recorded by the system. With respect to Petri net models, such invisible tasks might also be introduced for routing purposes (i.e., to preserve bipartiteness), or emerge from

[1]The complete event is one of the event type categories referring to the life cycle of an activity, standardized by the common XML format for workflow logs used by the ProM framework (refer to *http://www.processmining.org* for further information and the schema definition).

the conversion from other process model representations, such as Causal matrices [28] or EPCs [17].

In the remainder of this paper invisible tasks are characterized as bearing no label (since there is no log event associated) and denoted as a black rectangle.

0-to-1 mapping There is no task associated with the log event, the logged event does not correspond to a task in the model.

In the remainder of this paper it is abstracted from this case, assuming that the log has been pre-processed by deleting all events not having a correspondent in the process model.

1-to-n mapping One task is associated with multiple log events. This happens if the execution of a task is logged at a more fine-grained level, such as recording a task being scheduled, started, and finally completed.

Most information systems provide such detailed information through their logging facilities and as a next step one could make use of it to, e.g., explicitly detect parallelism. However, for the time being it is abstracted from this case, assuming that all but one log event have been discarded.

n-to-1 mapping Multiple tasks in the model are associated with the same type of log event, which are called *duplicate tasks*. It is important to understand that duplicate tasks only emerge from the mapping, since the tasks of a process model themselves *are* distinguishable, be it not by means of their label but their identity (which is reflected by their unique position in the graph). The presence of duplicate tasks is very likely for systems logging the invocation of an external application for the specific process instance[2] but without recording the associated model element (e.g., often models are only used as a reference for implementing the actual control flow logic). In such a situation, mapping a model containing two alternative paths that invoke the same "archive" application onto a corresponding log leads to two duplicate "archive" tasks.

In the remainder of this paper duplicate tasks are characterized as bearing the same label, which corresponds to the label of their—jointly—associated log event type.

As far as terminology is concerned the definitions provided in [2] are respected. In the context of Petri net models the term *task*, being a well-defined step in the process model, is interchangeably used with the corresponding Petri net term *transition*. An *activity* corresponds to the execution of a task for a specific case by a specific resource, which could be related to the occurrence of a log event (i.e., an audit trail entry).

[2] In fact, in ERP systems such as SAP R/3 or PeopleSoft it is often very difficult to even associate the logged events with a specific case [19].

3 Conformance Metrics

In the course of this section a set of conformance metrics will be defined, using the running example introduced in Section 3.1 to motivate the decisions made. Then the existence of two dimensions of conformance, fitness and appropriateness, is emphasized in Section 3.2, and three approaches to measure them are presented in Section 3.3 and Section 3.4. Afterwards, an interim evaluation takes place in Section 3.5 and it will turn out that the metrics defined lack certain desirable properties. Due to this fact two improved appropriateness metrics will be defined in Section 3.6, and a final evaluation of the findings concludes the section in Section 3.7.

3.1 Running Example

The example model used throughout the paper concerns the processing of a liability claim within an insurance company (see Figure 3.1). It sketches a fictive (but possible real-world) procedure and exhibits typical control flow constructs being relevant in the context of conformance testing.

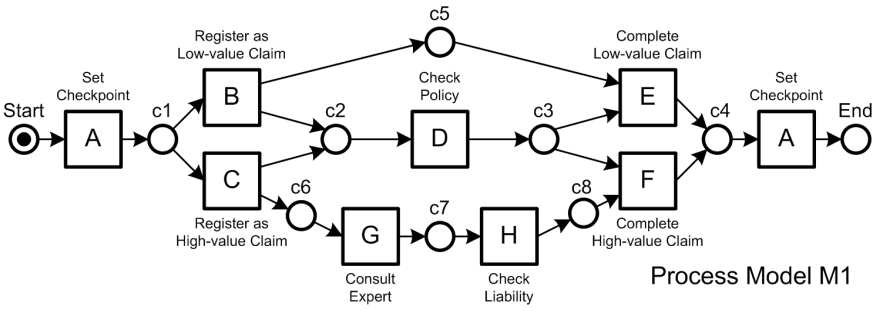


Figure 3.1: Simplified model of processing a liability insurance claim

At first there are two tasks bearing the same label “Set Checkpoint”. This can be thought of as an automatic backup action within the context of a transactional system, i.e., activity A is carried out at the beginning to define a rollback point enabling atomicity of the whole process, and at the end to ensure durability of the results. Then the actual business process is started with the distinction of low-value claims and high-value claims, which get registered differently (*B* or *C*). The policy of the client is checked anyway (*D*) but in the case of a high-value claim, additionally, the consultation of an expert takes place (*G*), and then the filed liability claim is being checked in more detail (*H*). The two completion tasks E and F can be thought of as two different sub-processes involving decision making and potential payment, taking place in another department. Note that the choice between *E* and *F* is influenced by the former choice between *B* and *C*, and the model therefore does not belong to the class of free-choice nets [14].

Figure 3.2 shows three example logs for the process described in Figure 3.1 at an aggregate

level. This means that process instances exhibiting the same event sequence are combined as a logical log trace, memorizing the number of instances to weigh the importance of that trace. That is possible since only the control flow perspective is considered here. In a different setting like, e.g., mining social networks [5], the resources performing an activity would distinguish those instances from each other.

No. of Instances	Log Traces
4070	ABDEA
245	ACDGHFA
56	ACGDHFA

(a) Event Log L1

No. of Instances	Log Traces
1207	ABDEA
145	ACDGHFA
56	ACGDHFA
23	ACHDFA
28	ACDHFA

(b) Event Log L2

No. of Instances	Log Traces
24	BDE
7	AABHF
15	CHF
6	ADBE
1	ACBGDFAA
8	ABEDA

(c) Event Log L3

Figure 3.2: Three example logs

Note that none of the logs contains the sequence *ACGHDFA*, although the Petri net model would allow this. In fact it is highly probable that a log does not exhibit all possible sequences, since, e.g., the duration of activities or the availability of suitable resources may render some sequences very unlikely to occur. With respect to the example model one could think of task *D* as a standard task requiring a very low specialization level and task *G* and *H* as highly specialized and time-consuming checks, so that finishing *G* and *H* before *D* would be possible but practically may not happen. Note that, furthermore, the number of possible sequences generated by a process model may grow exponentially, in particular for a model containing concurrent behavior. For example, there are $5! = 120$ possible combinations for executing five tasks, and $8! = 40320$ for executing eight tasks that are parallel to each other.

Therefore, an event log cannot be expected to exhibit *all* possible sequences of the underlying behavioral model. Process mining techniques strive for weakening the notion of *completeness*, i.e., the amount of information a log needs to contain for being able to rediscover the underlying process model [8].

3.2 Two Dimensions of Conformance: Fitness and Appropriateness

Measurement can be defined as a set of rules to assign values to a real-world property, i.e., observations are mapped onto a numerical scale (see also Section 2.1). In the context of conformance testing this means to weigh the "distance" between the behavior actually observed in the workflow log and the behavior described by the process model. If the distance is zero, i.e., the real business process exactly complies with the specified behavior, one can say that the log *fits* the model. With respect to the example model *M1* this seems to apply for event log *L1*, since every log trace can be associated with a valid path from *Start* to *End*. In contrast, event log *L2* does not match completely as the traces *ACHDFA* and *ACDHFA* lack the execution of activity *G*, while event log *L3* does not even contain one trace corresponding to the specified behavior. Somehow *L3* seems to fit "worse" than *L2*, and the degree of fitness should be determined according to this

intuitive notion of conformance, which might vary for different settings.

But there is another interesting—rather qualitative—dimension of conformance, which can be illustrated by relating the process models *M2* and *M3*, shown in Figure 3.3 and Figure 3.4, to event log *L2*. Although the log fits both models quantitatively, i.e., the event streams of the log and the model can be matched perfectly, they do not seem to be *appropriate* in describing the insurance claim administration.

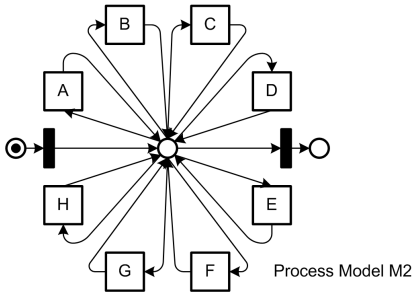


Figure 3.3: Workflow model on a too high level of abstraction (i.e., too generic)

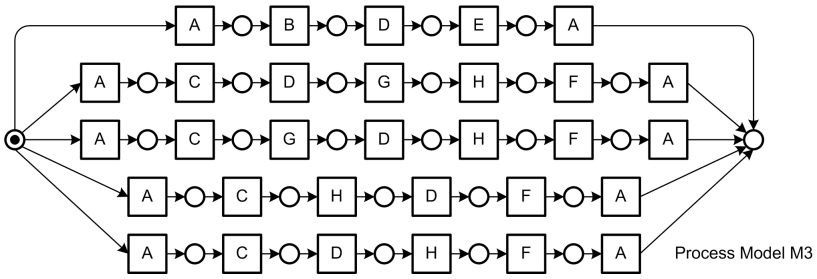


Figure 3.4: Workflow model on a too low level of abstraction (i.e., too specific)

The first one is much too generic as it covers a lot of extra behavior, allowing for arbitrary sequences containing the activities *A*, *B*, *C*, *D*, *E*, *F*, *G*, or *H*, while the latter does not allow for more sequences than those having been observed but only lists the possible behavior instead of expressing it in a meaningful way. Therefore, it does not offer a better understanding than can be obtained by just looking at the aggregated log. One can claim that a "good" process model should somehow be minimal in structure to clearly reflect the described behavior, in the following referred to as *structural appropriateness*, and minimal in behavior to represent as closely as possible what actually takes place, which will be called *behavioral appropriateness*.

Apparently, conformance testing demands for two different types of metrics, which are:

- *Fitness*, i.e., the extent to which the log traces can be associated with execution paths specified by the process model, and
- *Appropriateness*, i.e., the degree of accuracy in which the process model describes the observed behavior, combined with the degree of clarity in which it is represented.

3.3 Measuring Fitness

As mentioned in Section 2, one way to measure the fit between event logs and process models is to replay the log in the model and somehow measure the mismatch, which subsequently is described in more detail. The replay of every logical log trace starts with marking the initial place in the model and then the transitions that belong to the logged events in the trace are fired one after another. While doing so one counts the number of tokens that had to be created artificially (i.e., the transition belonging to the logged event was not enabled and therefore could not be *successfully executed*) and the number of tokens that had been left in the model, which indicates the process not having *properly completed*.

Metric 1 (Fitness) *Let k be the number of* different *traces from the aggregated log. For each log trace i ($1 \leq i \leq k$) n_i is the number of process instances combined into the current trace, m_i is the number of missing tokens, r_i is the number of remaining tokens, c_i is the number of consumed tokens, and p_i is the number of produced tokens during log replay of the current trace. The token-based fitness metric f is formalized as follows:*

$$f = \frac{1}{2}(1 - \frac{\sum_{i=1}^{k} n_i m_i}{\sum_{i=1}^{k} n_i c_i}) + \frac{1}{2}(1 - \frac{\sum_{i=1}^{k} n_i r_i}{\sum_{i=1}^{k} n_i p_i})$$

Note that, for all i, $m_i \leq c_i$ and $r_i \leq p_i$, and therefore $0 \leq f \leq 1$. To have a closer look at the log replay procedure consider Figure 3.5, which depicts the replay of the first trace from event log *L2* in process model *M1*. At the beginning (a) one initial token is produced for the *Start* place of the model ($p = 1$). The first log event in the trace, *A*, is associated with two transitions in the model (each bearing the label *A*—according to Section 2.3 they are called *duplicate tasks*). However, only one of them is enabled and thus will be fired (b), consuming the token from *Start* and producing one token for place *c1* ($c = 1, p = 2$). Now the next log event can be examined. The corresponding transition *B* is enabled and can be fired (c), consuming the token from *c1* and producing one token each for *c2* and *c5* ($c = 2, p = 4$). Then, the following log event corresponds to transition *D*, which is enabled and therefore can be fired (d), consuming the token from *c2* and producing a token for *c3* ($c = 3, p = 5$). Similarly, the transition associated to the next log event *E* is also enabled and fired (e), consuming the token from *c3* and *c5*, and producing one token for *c4* ($c = 5, p = 6$). Finally, the last log event is of type *A* again, i.e., is associated with the two transitions *A* in the model. But once more only one of them is enabled and therefore chosen to be fired (f), consuming the token from *c4* and producing one token for the *End* place ($c = 6, p = 7$). As a last step this token at the *End* place is consumed ($c = 7$) and the replay for that trace is completed. There were neither tokens missing nor remaining ($m = 0, r = 0$), i.e., this trace is perfectly fitting the model *M1*. Similarly, the second and third trace can also be perfectly replayed, i.e., neither tokens are missing nor remaining ($m_2 = m_3 = r_2 = r_3 = 0$).

Now consider Figure 3.6, which depicts the replay of the fourth trace from event log *L2* in *M1*. At the beginning (a)(b) the procedure is very similar, only that—instead of transition *B*—transition *C* is fired (c), consuming the token from *c1* and producing one token each for *c2* and c6 ($c = 2, p = 4$). But examining the next log event it turns out that its corresponding transition *H* is not enabled. Consequently, the missing token in *c7* is artificially created and recorded

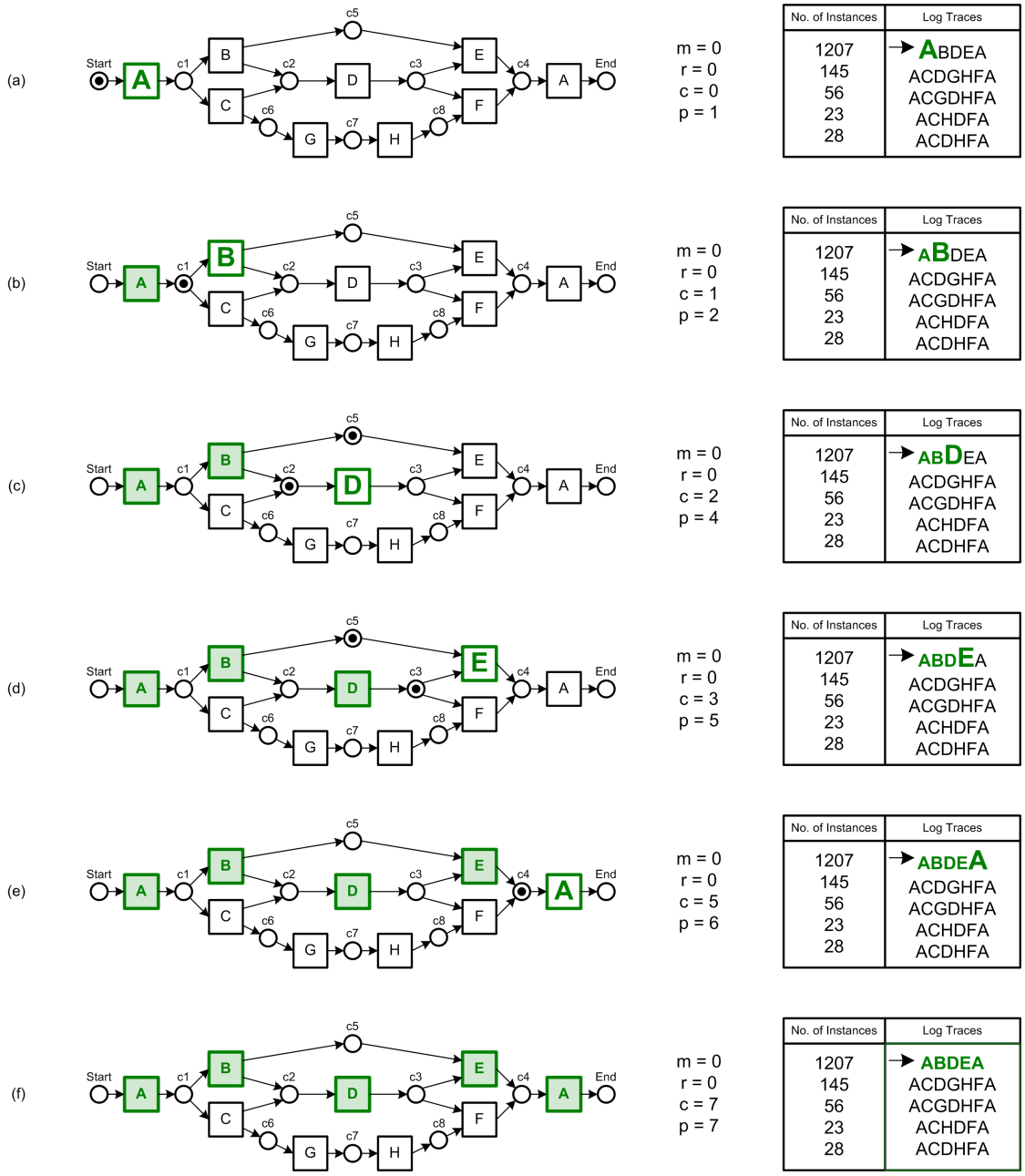


Figure 3.5: Log replay for trace $i = 1$ of event log *L2* in process model *M1*

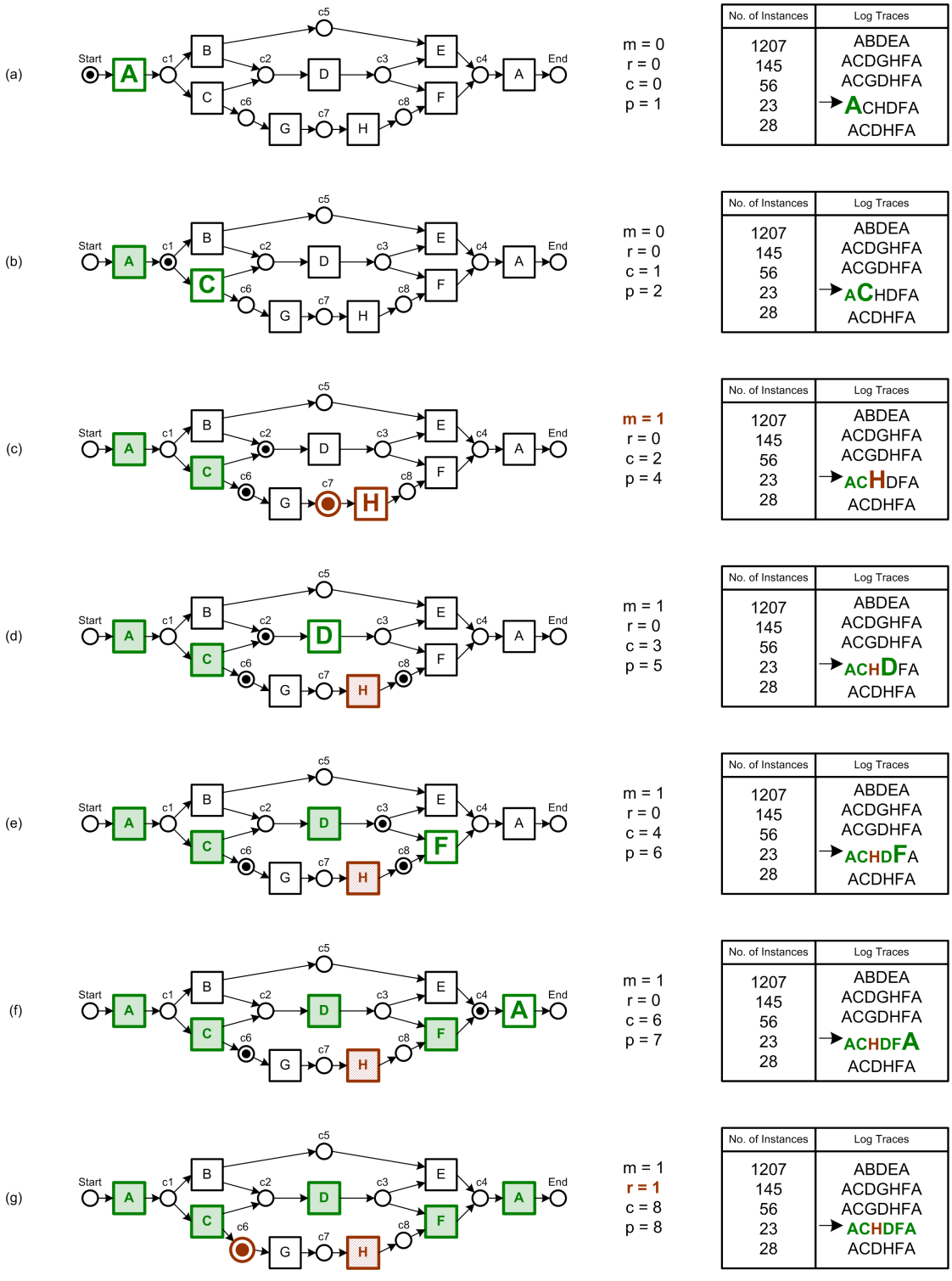


Figure 3.6: Log replay for trace $i = 4$ of event log *L2* in process model *M1*

($m = 1$), and the transition is fired (d), consuming it and producing one token for place *c8* ($c = 3, p = 5$). In contrast, the following log events can be successfully replayed again, i.e., their associated transitions are enabled and can be fired: (e) transition *D* consumes the token from *c2* and produces one token for *c3* ($c = 4, p = 6$), (f) transition *F* consumes the token from *c8* and *c3* and produces one token for *c4* ($c = 6, p = 7$), (g) one of the two associated transitions *A* is enabled and can be fired, consuming the token from *c4* and producing one token for the *End* place ($c = 7, p = 8$). At last the token at the *End* place is consumed again ($c = 8$). But then there is still a token remaining in place *c6*, which will be punished as it indicates that the process did not complete properly ($r = 1$). A similar problem will be encountered replaying the last trace of event log *L2*. Again, the model *M1* requires the execution of task *G* but this did not happen, and therefore a token is remaining in place *c6* ($r_5 = 1$) and a token is missing in place *c7* (m_5 = 1).

Using the metric f one can now calculate the fitness between the whole event log *L2* and the process description *M1*. As stated before, besides trace $i = 4$ only the last log trace $i = 5$ had tokens missing and remaining. Counting also the number of tokens being produced and consumed while replaying the other three traces (i.e., $c_2 = c_3 = p_2 = p_3 = 9$, and $c_5 = p_5 = 8$), and with the given number of process instances per trace, the fitness can be measured as $f(M1, L2) = 1 - \frac{23+28}{(1207 \cdot 7)+((145+56) \cdot 9)+((23+28) \cdot 8)} \approx 0.995$. Similarly, one can calculate the fitness between the event logs *L1*, *L3*, and the process description *M1*, respectively. The first event log *L1* shows three different log traces that all correspond to possible firing sequences of the Petri net with one initial token in the *Start* place. Thus, there are neither tokens left nor missing in the model during log replay and the fitness measurement yields $f(M1, L1) = 1$. In contrast, for the last event log *L3* none of the traces can be associated with a valid firing sequence of the Petri net and the fitness measurement yields $f(M1, L3) \approx 0.540$.

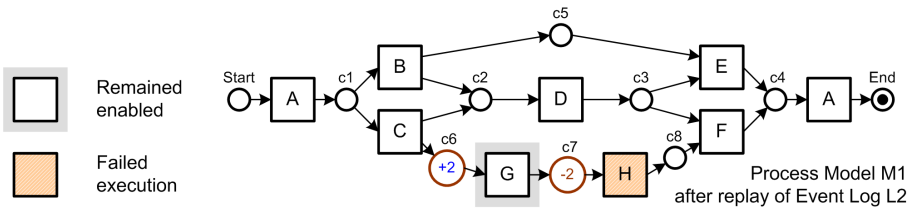


Figure 3.7: Diagnostic token counters provide insight into the location of errors

Besides measuring the degree of fitness pinpointing the site of mismatch is crucial for giving useful feedback to the analyst. In fact, the place of missing and remaining tokens during log replay can provide insight into problems, such as Figure 3.7 visualizes some diagnostic information obtained for event log *L2*. Because of the remaining tokens (whose amount is indicated by a $+$ sign) in place *c6* transition *G* has stayed enabled, and as there were tokens missing (indicated by a $-$ sign) in place *c7* transition *H* has failed seamless execution. Regarding evaluation of potential alignment procedures, the model rather lacks the possibility to skip activity *G* than that the expert consultation would be considered missing in almost half of the high-value claims that took place; however, a final interpretation could only be given by a domain expert from the

insurance company.

Note that this replay is carried out in a non-blocking way and from a log-based perspective, i.e., for each log event in the trace the corresponding transition is fired, regardless whether the path of the model is followed or not. This leads to the fact that—in contrast to directly comparing the event streams of models and logs—a concatenation of missing log events is punished by the fitness metric f just as much as a single one, since it could always be interpreted as a missing link in the model.

As described in Section 2.3, a prerequisite for conformance analysis is that modeled tasks must be associated with the logged events, which may result in *duplicate tasks*, i.e., multiple tasks that are mapped onto the same type of log event, and *invisible tasks*, i.e., tasks that have no corresponding log event. Duplicate tasks cause no problems during log replay as long as they are not enabled at the same time and can be executed (like shown in Figure 3.5 and Figure 3.6 for the two tasks labeled as *A*), but otherwise one must enable and/or fire the right task for progressing properly. Invisible tasks are considered to be lazy [28], i.e., they are only fired if they can enable the transition in question. In both cases it is necessary to partially explore the state space, which is described in more detail in Section 4.3.

3.4 Measuring Appropriateness

Generally spoken, determining the degree of appropriateness of a workflow process model strongly depends on subjective perception, and is highly correlated to the specific purpose. There are aspects like the proper semantic level of abstraction, i.e., the granularity of the described workflow actions, which can only be found by an experienced human designer. The notion of appropriateness addressed by this paper rather relates to the control flow perspective and therefore can be measured, although the measurement has a subjective element.

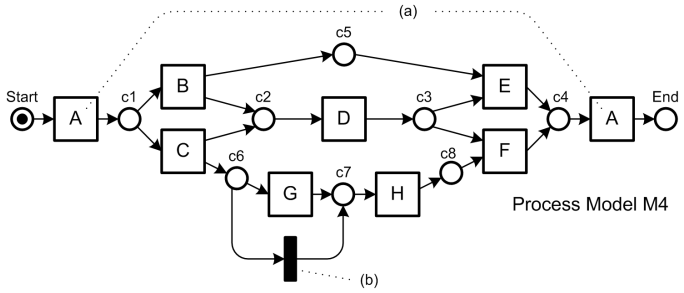


Figure 3.8: Model appropriate in structure and behavior

The overall aim is to have the model clearly reflect the behavior observed in the log, whereas the degree of appropriateness is determined by both structural properties of the model and the behavior described by it. Figure 3.8 shows *M4*, which appears to be a good model for the event log *L2* as it exactly generates the observed sequences in a structurally suitable way.

In the remainder of this section, both the structural and the behavioral part of appropriateness are considered in more detail.

3.4.1 Structural Appropriateness

The desire to model a business process in a compact and meaningful way is difficult to capture by measurement. As a first indicator a simple metric solely based on the graph size of the model will be defined, and subsequently some constructs that may inflate the structure of a process model are considered.

Metric 2 (Structural Appropriateness) *Let L be the set of labels, and N the set of nodes (i.e., places and transitions) in the Petri net model, then the structural appropriateness metric a_S is formalized as follows:*

$$a_S = \frac{|L| + 2}{|N|}$$

As described in Section 2.3 the mapping between modeled tasks and logged events is represented by a label denoting the associated log event type (if any) for each task. Given the fact that a business process model is expected to have a dedicated *Start* and *End* place (see the WF-net requirements in Section 2), the graph must contain at least one transition for every task label, plus two places (the start and end place). In this case $|N| = |L| + 2$ and the metric a_S yields the value 1. The more the size of the graph is growing, e.g., due to additional places, the measured value moves towards 0.

Calculating the structural appropriateness for the model *M3* yields $a_S(M3) \approx 0.170$, which is a very bad value caused by the many duplicate tasks (as they increase the number of transitions while having identical labels). For the good model *M4* the metric yields $a_S(M4) = 0.5$. With $a_S(M5) \approx 0.435$ a slightly worse value is calculated for the behaviorally (trace) equivalent model in Figure 3.9, which is now used to consider some constructs that may decrease the structural appropriateness a_S.

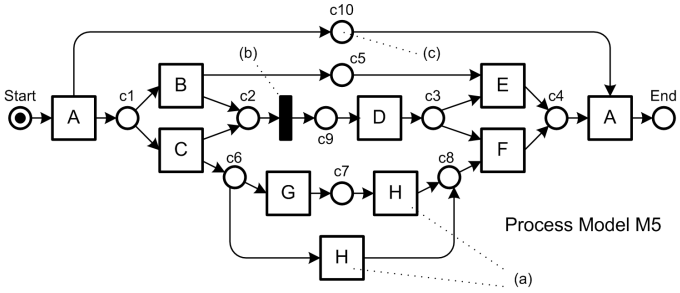


Figure 3.9: Structural properties may reduce the appropriateness of a model

(a) *Duplicate tasks.* Duplicate tasks that are used to list alternative execution sequences tend to produce models like the extreme *M3*. Figure 3.9 (process model *M5*) shows an example situation in which a duplicate task is used to express that after performing activity *C* either the sequence *GH* or *H* alone can be executed (see (a) in Figure 3.9). Figure 3.8 (process model *M4*) describes the same process with the help of an invisible task (see (b) in Figure 3.8), which is only used for routing purposes and therefore not visible in the log. One could argue that this model supports a more suitable perception namely activity *G* is not obliged to execute but can

be skipped, but it somehow remains a matter of taste. However, excessive usage of duplicate tasks for listing alternative paths reduces the appropriateness of a model in preventing desired abstraction.

In addition, there are also duplicate tasks that are necessary to, e.g., specify a certain activity taking place exactly at the beginning and at the end of the process like task *A* in process model *M4* (see (a) in Figure 3.8).

(b) *Invisible tasks*. Besides the invisible tasks used for routing purposes like, e.g., shown by (b) in Figure 3.8, there are also invisible tasks that only delay visible tasks, such as the one indicated by (b) in Figure 3.9. If they do not serve any model-related purpose they can simply be removed, thus making the model more concise.

(c) *Implicit places*. Implicit places are places that can be removed without changing the behavior of the model [8]. An example for an implicit place is given by place *c10* (see (c) in Figure 3.9). Again, one could argue that they should be removed as they do not contribute anything, but sometimes it can be useful to insert such an implicit place to, e.g., show document flows.

Note that the place *c5* in Figure 3.9 is not implicit as it influences the choice made later on between *E* and *F*. Both *c5* and *c10* are *silent places*, with a silent place being a place whose directly preceding transitions are never directly followed by one of their directly succeeding transitions (e.g., for *M4* it is not possible to produce an event sequence containing *BE* or *AA*). Mining techniques by definition are unable to detect implicit places, and have problems detecting silent places.

3.4.2 Behavioral Appropriateness

Besides the structural properties that can be evaluated on the model itself appropriateness can also be examined with respect to the behavior recorded in the log. Assuming that the log fits the model, i.e., the model allows for all the execution sequences present in the log, there remain those that would fit the model but have not been observed. Assuming further that the log satisfies some notion of completeness, i.e., the behavior observed corresponds to the behavior that should be described by the model, it is desirable to represent it as precisely as possible. When the model gets too general and allows for more behavior than necessary/likely (like in the "flower" model *M2*) it becomes less informative in actually describing the process.

One approach to measure the amount of possible behavior is to determine the mean number of enabled transitions during log replay. This corresponds to the idea that for models clearly reflecting their behavior, i.e., complying with the structural properties mentioned above, an increase of alternatives or parallelism and therefore an increase of potential behavior will result in a higher number of enabled transitions during log replay.

Metric 3 (Behavioral Appropriateness) *Let k be the number of* different *traces from the aggregated log. For each log trace i ($1 \leq i \leq k$) n_i is the number of process instances combined into the current trace, and x_i is the mean number of enabled transitions during log replay of the current trace (note that invisible tasks may enable succeeding labeled tasks but they are not*

counted themselves). Furthermore, m is the number of labeled tasks (i.e., does not include invisible tasks, and assuming $m > 1$) in the Petri net model. The behavioral appropriateness metric a_B is formalized as follows:

$$a_B = 1 - \frac{\sum_{i=1}^{k} n_i(x_i - 1)}{(m-1) \cdot \sum_{i=1}^{k} n_i}$$

Calculating the behavioral appropriateness with respect to event log *L2* for the model *M2* yields $a_B(M2, L2) = 0$, which indicates the arbitrary behavior described by it. For *M4*, which exactly allows for the behavior observed in the log, the metric yields $a_B(M4, L2) \approx 0.967$. As an example it can be compared with the model *M6* in Figure 3.10, which additionally allows for arbitrary loops of activity *G* and therefore exhibits more potential behavior. This is also reflected in the behavioral appropriateness measure as it yields a slightly smaller value than for the model *M4*, namely $a_B(M6, L2) \approx 0.964$.

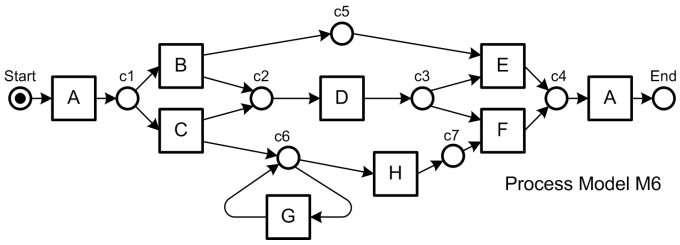


Figure 3.10: Unnecessary potential behavior may reduce the appropriateness of a model

3.5 Balancing Fitness and Appropriateness—an Interim Evaluation

Having defined the three metrics f, a_S, and a_B, the question is now how to put them together. This is not an easy task since they are partly correlated with each other. So the structure of a process model may influence the fitness metric f as, e.g., due to inserting redundant invisible tasks the value of f increases because of the more tokens being produced and consumed while having the same amount of missing and remaining ones. But unlike a_S and a_B the metric f defines an optimal value 1.0, for a log that can be parsed by the model without any error.

Therefore, it is recommended to carry out the conformance analysis in two phases. During the first phase the fitness of the log and the model is ensured, which means that discrepancies are analyzed and potential corrective actions are undertaken. If there still remain some tolerable deviations, the log or the model should be manually adapted to comply with the ideal or intended behavior, in order to go on with the so-called appropriateness analysis. Within this second phase the degree of suitability of the respective model in representing the process recorded in the log is determined.

Table 3.1: Diagnostic results

	M1	*M2*	*M3*	*M4*	*M5*	*M6*
L1	$f = 1.0$ $a_S = 0.5263$ $a_B = 0.9740$ $a = 0.5126$	$f = 1.0$ $a_S = 0.7692$ $a_B = 0.0$ $a = 0.0$	$f = 1.0$ $a_S = 0.1695$ $a_B = 0.9739$ $a = 0.1651$	$f = 1.0$ $a_S = 0.5$ $a_B = 0.9718$ $a = 0.4859$	$f = 1.0$ $a_S = 0.4348$ $a_B = 0.9749$ $a = 0.4239$	$f = 1.0$ $a_S = 0.5556$ $a_B = 0.9703$ $a = 0.5391$
L2	$f = 0.9952$ $a_S = 0.5263$ $a_B = 0.9705$	$f = 1.0$ $a_S = 0.7692$ $a_B = 0.0$ $a = 0.0$	$f = 1.0$ $a_S = 0.1695$ $a_B = 0.9745$ $a = 0.1652$	$f = 1.0$ $a_S = 0.5$ $a_B = 0.9669$ $a = 0.4835$	$f = 1.0$ $a_S = 0.4348$ $a_B = 0.9706$ $a = 0.4220$	$f = 1.0$ $a_S = 0.5556$ $a_B = 0.9637$ $a = 0.5354$
L3	$f = 0.5397$ $a_S = 0.5263$ $a_B = 0.8909$	$f = 1.0$ $a_S = 0.7692$ $a_B = 0.0$	$f = 0.4947$ $a_S = 0.1695$ $a_B = 0.8798$	$f = 0.6003$ $a_S = 0.5$ $a_B = 0.8904$	$f = 0.6119$ $a_S = 0.4348$ $a_B = 0.9026$	$f = 0.5830$ $a_S = 0.5556$ $a_B = 0.8894$

Regarding the example logs given in Figure 3.2 this means that an evaluation of the appropriateness measurements takes place only for those models having a fitness value $f = 1.0$ (cf. Table 3.1) and therefore event log *L3*, which only fits the trivial process model *M2*, is completely discarded, just like process model *M1* for event log *L2*. For event logs *L1* and *L2* now the most adequate process model should be found among the remaining ones, respectively. For this purpose a simple appropriateness metric, combining the structural and the behavioral part as a product (i.e., denoting the area within the unit square), is defined.

Metric 4 (Appropriateness) *Based on the structural appropriateness metric a_S and the behavioral appropriateness metric a_B the unified appropriateness metric a is defined as follows:*

$$a = a_S \cdot a_B$$

Examining the values of the unified appropriateness metric a in Table 3.1 it turns out that the model *M6* is selected as the most appropriate representation for the behavior observed in both the event log *L1* and *L2*, which is *not* in line with intuitive expectations. While looking for an answer, one can observe that for the extremely generic model *M2* the a_S value is always very high while the a_B value is very low and vice versa for the extremely specific model *M3*. So for finding the most appropriate process model it seems like both the structural appropriateness metric a_S and the behavioral appropriateness metric a_B must be understood as an indicator to be maximized without decreasing the other. However, balancing them will always be difficult as they are correlated with each other, which becomes clear reconsidering the assumptions the metrics are based on.

The motivation for measuring the amount of potential behavior via the mean number of enabled transitions during log replay was explicitly based on the assumption that the structure of the process model clearly reflects the behavior which is expressed by it. This means that the metric a_B is limited in its applicability, since the fundamental idea that adding alternative or

parallel behavior to a Petri net will increase the mean number of enabled transitions during log replay only holds for a certain class of process models. As soon as a process model is strongly sequentialized using alternative duplicate tasks, such as it is the case for the extremely specific model *M3*, the assumption does not hold anymore and the result becomes meaningless. One can further observe that the model *M4* yields a worse a_B value than the model *M5* although they are behaviorally (trace) equivalent. This shows that the metric a_B is affected by structural properties, which violates the stability requirement (see Requirement 2 in Section 2.1).

But also the metric a_S, which should only measure the structural appropriateness, is not independent of the behavioral expressiveness of a model. The very good a_S value for process model *M2* shows that it is easy to make a model more compact while rendering it more generic in behavior. Imagine a natural language where (for any reason such as faster speaking, or a lack of space in writing) the suitability of using a word is based on the number of letters it is formed of. The shorter word among two words can then, however, only be considered the better if they both *mean* the same. Following this analogy, there is the implicit assumption that it makes only sense to compare models based on their graph size if they somehow allow for the same amount of behavior (which violates the stability requirement, too).

Revising the other requirements imposed in Section 2.1 one will detect that also the analyzability requirement (see Requirement 3) is not fulfilled with respect to a_S and a_B. The measured values do not seem to be very well distributed (note that the behavioral appropriateness value a_B, except for the extreme *M2*, is always around 0.96 or 0.97 with respect to *L1* and *L2*), and although it is possible to reach the optimal value 1 this is not guaranteed for an optimal solution. For example, one would expect the process model *M1* having an optimal structure, as a more compact representation of the behavior specified does not seem feasible. However, the structural appropriateness $a_S(M1)$ only yields 0.5263. Similarly, model *M4* precisely specifies the behavior observed in event log *L2*, but still $a_B(M4, L2)$ only yields 0.9669, which suggests that there would be a better solution.

As a comparative means and within the class of process models where their respective assumptions are fulfilled, the presented metrics can be very well applied. So can the a_S metric be used to find out that the process model *M4* corresponds to a structurally more suitable representation than *M3* and *M5*. The a_B metric determines *M1*, the initial Petri net given in Figure 3.1, as the behaviorally most suitable model over *M2*, *M4*, and *M6* for the event log *L1*. Similarly, *M4* is considered behaviorally more suitable than *M2* or *M6* for event log *L2*.

However, to extend the applicability it would be useful to have an independent measure for both structural and behavioral appropriateness, i.e., meeting Requirement 2, and to also reach an optimal point, indicating that there is no better solution available, i.e., meeting Requirement 3.

3.6 Alternative Approaches for Measuring Appropriateness

Based on the insight gained into the weak points of the appropriateness metrics defined so far the aim is now to find alternative metrics, which are independent (i.e., not affected by properties that should not be measured) and better distribute possible values between 0 and 1 (in particular define an optimal value). In the following an alternative approach for both measuring structural

and behavioral appropriateness is presented.

3.6.1 Structural Appropriateness

When defining a metric for measuring structural appropriateness one might be tempted to favor a specific behavioral pattern [3], e.g., the Sequence, over others, for reasons such as approximating the most common behavior or just to "make the examples work". But actually, structure must be seen as the syntactic means by which behavior (i.e., the semantics) may be specified at all. When using Petri nets to model business processes like every language this is formed by the vocabulary (i.e., places, transitions, and edges) combined with a set of rules (such as the bipartiteness requirement).

Often there are several syntactic ways to express the same behavior and the challenge of a structural appropriateness metric is to verify certain design guidelines, which define the *preferred* way to express a certain behavioral pattern, and to somehow punish their violations. It is obvious that these design guidelines will vary for different process modeling notations and may depend on personal or corporate preferences. However, to demonstrate the character of an independent structural appropriateness metric the findings of Section 3.4.1 will be used to define an alternative metric a'_S. As a design guideline, constructs such as *alternative duplicate tasks* and *redundant invisible tasks* should be avoided as they were identified to inflate the structure of a process model and to detract from clarity in which the expressed behavior is reflected.

As the definition of these constructs requires an analysis of the state space of the process model, some preparative definitions are provided in the following.

Definition 1 (Labeled Transition System) *A labeled transition system is defined as* $TS = (S, E, T, L, l)$ *where* S *is the set of states,* $E \subseteq (S \times T \times S)$ *is the set of state transitions,* T *the set of transition names,* L *a set of transition labels, and* $l \in T \not\to L$ *is a partial labeling function (only the transitions in* $dom(l)$ *are visible). It is assumed to have a unique start state* Start *and end state* End*.*

Definition 2 (Paths and Projection) *Given a labeled transition system* $TS = (S, E, T, L, l)$*:*

- $paths(TS) \subseteq T^*$ *is the set of paths in* TS *(a path* p *being defined as a sequence of length* $len(p)$*, i.e.,* $p = (p_0, \ldots, p_{len(p)-1})$*) starting in state* Start *and ending in state* End*,*
- *for all* $p \in paths(TS)$*,* $proj(p)$ *is the projection of* p *onto* L*, i.e., visible transitions are relabeled using* l *while invisible transitions are removed, and*
- $projection(TS) = \{proj(p) \mid p \in paths(TS)\}$.

A labeled transition system TS will be used to represent the state space of the process model. Then $paths(TS)$ denotes the set of possible execution sequences with respect to that model while $projection(TS)$ represents the set of traces that could be possibly observed in a log (as, like stated in Section 2.3, the label serves as a mapping between modeled tasks and log events).

Now the alternative duplicate tasks and redundant invisible tasks are defined and the alternative metric a'_S is presented.

Definition 3 (Alternative Duplicate Tasks) *Let $TS = (S, E, T, L, l)$ be the labeled transition system denoting the state space of a Petri net model, and D^{lab} the set of duplicate tasks bearing the same label lab, then the set of Alternative Duplicate Tasks D_A is defined as follows:*

$$A_D^{lab} = \{(x, y) \in D^{lab} \times D^{lab} \mid \neg\exists_{p \in paths(TS)} (\exists_{0 \leq i < j < len(p)} ((x \neq y) \wedge ((p_i = x \wedge p_j = y) \vee (p_i = y \wedge p_j = x))))\},\ lab \in L \quad (3.1)$$

$$D_A^{lab} = \begin{cases} \emptyset & \text{if } A_D^{lab} = \emptyset \\ D^{lab} & \text{if } A_D^{lab} \neq \emptyset \end{cases},\ lab \in L \quad (3.2)$$

$$D_A = \bigcup_{lab \in L} D_A^{lab} \quad (3.3)$$

Equation 3.1 defines a relation A_D^{lab} over the cross product of a set of equally labeled tasks D^{lab}, selecting those pairs that are never contained together in one possible execution path, i.e. are *alternative* to each other. Only different transitions are considered, and therefore sets D^{lab} with only one transition contained (i.e., non-duplicates) will result in $A_D^{lab} = \emptyset$. A set of duplicate tasks containing more than two transitions is considered alternative as soon as there are two tasks contained that are alternative to each other. This is reflected by Equation 3.2 as either $D_A^{lab} = D^{lab}$, if the corresponding alternative duplicates relation A_D^{lab} is not empty, or is set to the empty set. Finally, in Equation 3.3 all the sets of alternative duplicate tasks from the process model are merged, which is denoted by D_A.

Note that according to the definition the duplicate tasks indicated by (a) in Figure 3.8 are not alternative, and therefore are not contained in D_A.

Definition 4 (Redundant Invisible Tasks) *Let $TS = (S, E, T, L, l)$ be the labeled transition system denoting the state space of a Petri net model, and I the set of invisible tasks (i.e., $I = \{t \in T \mid t \notin dom(l)\}$). Given TS and a $t \in T$: $merge(TS, t)$ is the labeled transition system resulting from merging the source and target nodes of all edges referring to t, i.e., for any $(s_1, t, s_2) \in E$, states s_1 and s_2 are merged. The set of Redundant Invisible Tasks I_R is defined as follows:*

$$I_R = \{t \in I \mid projection(TS) = projection(merge(TS, t))\} \quad (3.4)$$

The idea behind a *redundant* invisible task is that it can somehow be removed from the model without affecting the set of possibly generated traces, i.e., the $projection$. Since defining this property on the graph level (i.e., the Petri net level) is a bit more involved, the definition makes use of merging states in the corresponding transition system, such that the specific transition is not contained anymore. Then in Equation 3.4 for each invisible task of the model is checked whether the set of possible traces of the modified transition system is the same as for the initial transition system. If so, the task is considered redundant and thus included into I_R.

According to this definition the invisible task contained in model *M4* (see (b) in Figure 3.8) is not redundant as via merging its source and target states the corresponding labeled transition system would additionally allow for traces containing arbitrary sequences of *G*.

Another requirement is covered by the implicit assumption that the transition system resulting from the $merge$ operation must still have a unique *Start* start and a unique *End* state. The reason for this is that, e.g., the invisible tasks contained in model *M2* are not redundant as removing them would lead to a process model without having a dedicated *Start* and *End* place, i.e., it would not be a WF-net anymore.

Metric 5 (Improved Structural Appropriateness) *Let T be the set of transitions in the Petri net model, then the improved structural appropriateness metric a'_S is formalized as follows:*

$$a'_S = \frac{|T| - (|D_A| + |I_R|)}{|T|}$$

Note that $|D_A| + |I_R| \leq |T|$ and therefore $0 \leq a'_S \leq 1$ as duplicate tasks are always visible. Revising the example models it turns out that, according to the defined design guideline, only model *M5* and *M3* are reduced in structural appropriateness. For *M5* the number of alternative duplicate tasks $|D_A| = 2$ (see (a) in Figure 3.9) and the number of redundant invisible tasks $|I_R| = 1$ (see (b) in Figure 3.9), which results in $a'_S(M5) \approx 0.727$. In *M3* all tasks but *B* belong to the set of alternative duplicate tasks and therefore $a'_S(M3) \approx 0.032$.

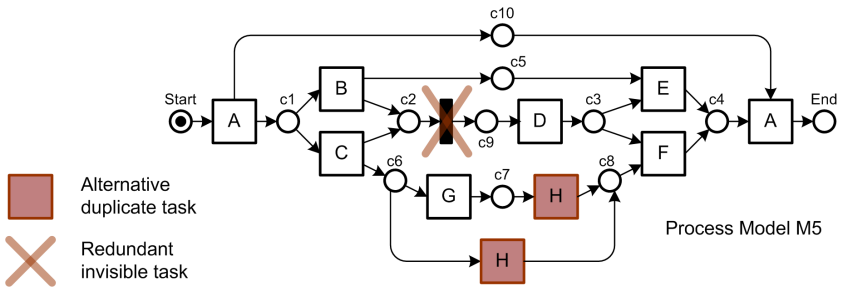


Figure 3.11: Design guideline violations can be visualized

Finally, a very important point is that building a notion of structural appropriateness with the help of some kind of design guideline usually enables the visualization of its violations (see Figure 3.11). This demonstrates that metric a'_S—in contrast to metric a_S—meets the localizability requirement (see Requirement 5 in Section 2.1).

3.6.2 Behavioral Appropriateness

To approach behavioral appropriateness independently from structural properties the potential behavior specified by the model will be analyzed and compared with the behavior *actually needed* to describe what has been observed in the log. In order to somehow measure their "distance" a set of relations can be derived from both the process model (analyzing the possible execution sequences) and the event log (analyzing the observed execution sequences). When referring to the traces generated by the process model Definition 2 and Definition 1 from Section 3.6.1 will be reused.

Definition 5 (Always and Never Relation Forwards and Backwards) *Let L be the set of all labels (including an artificially inserted* Start *and* End *task or log event, respectively). P_L is either $projection(TS)$ for TS representing the labeled transition system for the process model or the set of all traces contained in the event log, respectively. The Always Relation Forwards A_F, the Never Relation Forwards N_F, the Always Relation Backwards A_B, and the Never Relation Backwards N_B are formalized as follows:*

$$P_L(x) = \{p \in P_L \mid \exists_{0 \leq i < len(p)}\ p_i = x\},\ x \in L \tag{3.5}$$

$$\begin{aligned} A_F &= \{(x,y) \in L \times L \mid \\ &\quad (P_L(x) \neq \emptyset) \wedge (\forall_{p \in P_L(x)}\ (\exists_{0 \leq i < j < len(p)}\ (p_i = x \wedge p_j = y)))\} \end{aligned} \tag{3.6}$$

$$N_F = \{(x,y) \in L \times L \mid \neg\exists_{p \in P_L}\ (\exists_{0 \leq i < j < len(p)}\ (p_i = x \wedge p_j = y))\} \tag{3.7}$$

$$\begin{aligned} A_B &= \{(x,y) \in L \times L \mid \\ &\quad (P_L(x) \neq \emptyset) \wedge (\forall_{p \in P_L(x)}\ (\exists_{0 \leq j < i < len(p)}\ (p_i = x \wedge p_j = y)))\} \end{aligned} \tag{3.8}$$

$$N_B = \{(x,y) \in L \times L \mid \neg\exists_{p \in P_L}\ (\exists_{0 \leq j < i < len(p)}\ (p_i = x \wedge p_j = y))\} \tag{3.9}$$

As discussed in Section 2.3 in the scope of this paper the set of labels L serves as a link between the model task identifiers and the elements contained in the log, denoting the mapping that has been established. Furthermore, it was assumed that log events not referring to any task in the model were removed from the log. In doing so it is possible to derive comparable relations from both the model and the log perspective.

While building the relations for the model recall that invisible tasks are defined unlabeled and thus are not covered by L. What is more, duplicate tasks bear the same label and consequently are represented only once within L. This leads to the fact that if there are three duplicate tasks x_1, x_2, and x_3 jointly labeled with x the expressions involving x decompose to $x_1 \vee x_2 \vee x_3$, i.e., the successor or predecessor relationship between two label elements is acknowledged as soon as it holds for *any* of the duplicates. Clearly during this projection some information is lost, namely which precise task was considered successor or predecessor, but this is logically consistent as the relations will be verified with respect to the log, which does not allow for this distinction either.

Note that the successor relationship (cf. Forwards relations) and the predecessor relationship (cf. Backwards relations) are defined *globally*, i.e., are acknowledged as soon as they hold for *any* pair of labels. To give an example imagine a path $p = (\ldots, x, \ldots, x, \ldots, y, \ldots, x, \ldots)$. Here the global successor-ship would be confirmed for the tuple (x, y) although it does not hold for all x that it is followed by y, and although they do not *directly* follow each other. This is motivated by the desire to also capture global behavioral dependencies, which, e.g., may be introduced by non-free-choice constructs [14], and to recognize a behavioral constraint that only involves one transition out of a set of duplicate tasks.

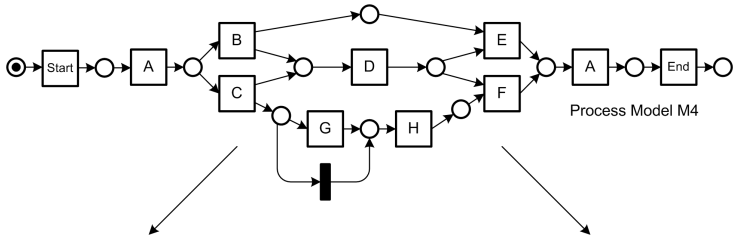
Note further that the insertion of an artificial *Start* and *End* task (or log event, respectively) is only needed to capture the special case of alternative paths leading directly from the *Start* place to the *End* place of the model, and therefore can be left out if this does not apply.

Definition 6 (Sometimes Relation Forwards and Backwards) *Let L be the set of all labels (including an artificially inserted* Start *and* End *task or log event, respectively), then the Sometimes Relation Forwards S_F and the Sometimes Relation Backwards S_B are formalized as follows:*

$$S_F = (L \times L) \setminus (A_F \cup N_F) \tag{3.10}$$

$$S_B = (L \times L) \setminus (A_B \cup N_B) \tag{3.11}$$

Based on the previously defined relations A_F and N_F the relation S_F can be defined (see Equation 3.10). Together they state for each pair of labels (x, y) whether y either *always*, or *never*, or *sometimes* follows x; with respect to the set possible execution paths (model perspective) or the set of log traces (log perspective), correspondingly. Analogously S_B is defined via A_B and N_B (see Equation 3.11), intuitively stating for each pair of labels (x, y) whether y either *always*, or *never*, or *sometimes* precedes x. Note that due to the additional requirement $P_L(x) \neq \emptyset$ in Equation 3.6 A_F, N_F, and S_F indeed partition $L \times L$. Similarly, A_B, N_B, and S_B partition $L \times L$ due to Equation 3.8. $P_L(x)$ is empty if log event x has not been observed as, e.g., an alternative branch has always been decided in the same way (and therefore the task labeled x has never been executed). If the requirement was dropped, in such a case all the tuples $(x, ...)$ were contained in both relation A_F and relation N_F (the same holds for A_B and N_B). However, as the formation of the new behavioral appropriateness metric later in this section will only be based on the relations S_F and S_B the requirement is not really necessary and rather was added in order to correspond to intuition.



F	Start	A	B	C	D	E	F	G	H	End
Start	N	A	S	S	A	S	S	S	S	A
A	N	A	S	S	A	S	S	S	S	A
B	N	A	N	N	A	A	N	N	N	A
C	N	A	N	N	A	N	A	S	A	A
D	N	A	N	N	N	S	S	S	S	A
E	N	A	N	N	N	N	N	N	N	A
F	N	A	N	N	N	N	N	N	N	A
G	N	A	N	N	S	N	A	N	A	A
H	N	A	N	N	S	N	A	N	N	A
End	N	N	N	N	N	N	N	N	N	N

B	Start	A	B	C	D	E	F	G	H	End
Start	N	N	N	N	N	N	N	N	N	N
A	A	A	S	S	A	S	S	S	S	N
B	A	A	N	N	N	N	N	N	N	N
C	A	A	N	N	N	N	N	N	N	N
D	A	A	S	S	N	N	N	S	S	N
E	A	A	A	N	A	N	N	N	N	N
F	A	A	N	A	A	N	N	A	A	N
G	A	A	N	A	S	N	N	N	N	N
H	A	A	N	A	S	N	N	S	N	N
End	A	A	S	S	A	S	S	S	S	N

Figure 3.12: Deriving the "footprint" from a process model

Together the defined relations can be considered being a (left and a right) "footprint" (see also Figure 2.1) of the behavior represented. As an example, consider Figure 3.12 where the Forwards relations and the Backwards relations are derived for the process model *M4* and depicted in the F matrix and B matrix, respectively.

Both the S_F and S_B relation are highlighted as they indicate concurrent or alternative behavior. Parallel tasks may follow each other in any order, such that (D, G), (D, H), (G, D), and (H, D) are contained in both relation S_F and relation S_B. Alternative paths are also reflected by tuples contained in the Sometimes relations: Tasks preceding an alternative branch can be followed by any of the alternative paths, and therefore—together with the tasks contained in those paths—form part of the Sometimes Relation Forwards, i.e., $(Start, B)$, $(Start, E)$, $(Start, C)$, $(Start, G)$, $(Start, H)$, $(Start, F)$, (A, B), (A, E), (A, C), (A, G), (A, H), (A, F), (C, G), (D, E), and $(D, F) \in S_F$. Similarly, the tasks succeeding the alternative join can be preceded by any of the alternative paths, and therefore—together with the tasks contained in those paths—form part of the Sometimes Relation Backwards, i.e., (End, E), (End, B), (End, F), (End, H), (End, G), (End, C), (A, E), (A, B), (A, F), (A, H), (A, G), (A, C), (H, G), (D, B), and $(D, C) \in S_B$.

Note that this asymmetry with respect to alternative behavior is also the motivation for including both directions in the improved behavioral appropriateness metric that will be defined later on in this section. If one would only evaluate one of them, the position of, e.g., an unused alternative path in the model (such as close to the Start place or close to the End place) would affect the measured value, which would violate Requirement 2 from Section 2.1.

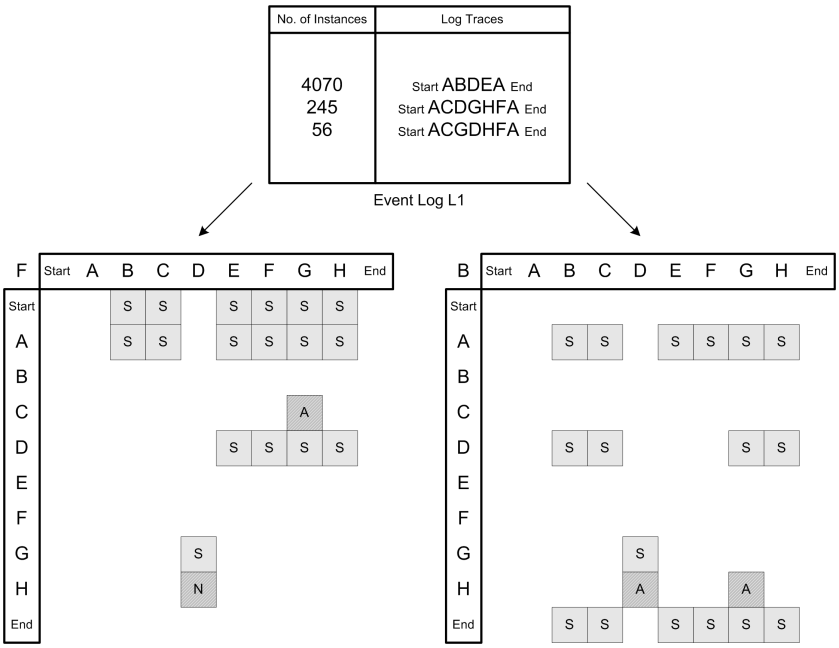


Figure 3.13: Matching the model "footprint" with the one from the log

Now consider Figure 3.13, where the S relations of the model in Figure 3.12 have been matched with the "footprint" of the log *L1*. Note that it is sufficient to compare the elements derived from the S relations of the model with the corresponding tuples of the relations derived from the log. For evaluating behavioral appropriateness it is solely relevant to find out in which place the log becomes more specific, i.e., the model allows for more behavior than necessary. In Figure 3.13 this is the case for two tuples each in the S_F and in the S_B relation.

First, the tuple (H, D) becomes an element of the N_F relation (instead of S_F), and (H, D) becomes an element of A_B (instead of S_B), which is caused by the fact that, although according to the model task *D* and *H* are concurrent and could be executed in any order, finishing *D* after *H* has never happened. Second, the tuple (C, G) becomes an element of the A_F relation (instead of S_F) and (H, G) becomes an element of A_B (instead of S_B). This is caused by the fact that the process model allows to skip activity *G*, which has never been used by the process observed in event log *L1*.

Apparently, this behavioral appropriateness analysis approach is able to highlight unused alternative and concurrent behavior, which can also be visualized in some way (see Figure 3.14). This demonstrates that it—in contrast to the approach presented in Section 3.4.2—meets the localizability requirement (see Requirement 5 in Section 2.1).

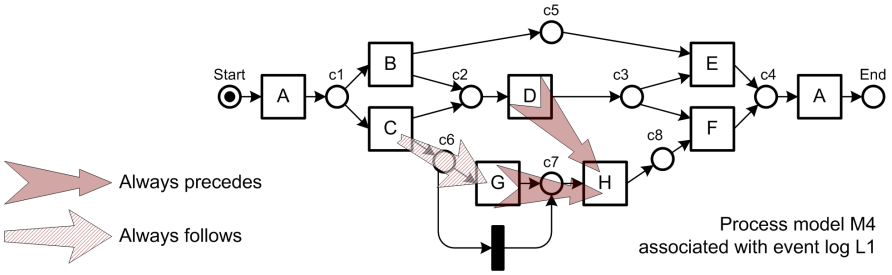


Figure 3.14: Restricted relationships can be visualized

However, interpretation of these results may vary and can only be accomplished by a domain expert as for analysis the log is assumed to be *complete*[1], i.e., to somehow exhibit all the behavior that can happen according to the underlying process model. Like already discussed in Section 3.1 this is not necessarily the case.

According to the example process observed in event log *L1* task *D* and task *H* are not executed in parallel. However, the control flow of a process model represents causal dependencies, i.e., a partial ordering, among a set of tasks. Therefore, a possible interpretation could be that they are not causally related to each other, i.e., they *are* concurrent from a modeling point of view. Consequently, the indicated problem results from the log not being complete. Similarly,

[1]Note that the notion of completeness applied here corresponds to a slightly weaker assumption than the definition provided in [8] in the context of process mining. They both do not require all possible sequences being present in the log (which, as already discussed, would be a very strong assumption) but call for every two tasks that potentially follow each other to actually do so in some trace. The notion assumed for this behavioral appropriateness approach is slightly weaker in the sense that the successor-ship property is evaluated *globally* instead of assuming the events *directly* following each other.

the possibility to skip activity *C* was not used while handling more than 4300 instances but still could be interpreted as a rare exceptional behavior, which has not been observed. This indicates that completeness is a problem inherent to any behavioral appropriateness approach, and that a final interpretation of the results obtained can only be given by an experienced business analyst.

The improved approach to quantify behavioral appropriateness is based on the cardinal numbers of the Sometimes relations, which corresponds to the idea that increasing the potential behavior of a model, i.e., adding alternatives or concurrency, will lead to an increased number of elements being contained in S_F and/or S_B.

Metric 6 (Improved Behavioral Appropriateness) *Let L be the set of all labels (including an artificially inserted* Start *and* End *task or log event, respectively), $max = |L|^2 - 3|L| + 2$, S_F^m the S_F relation and S_B^m the S_B relation for the process model, and S_F^l the S_F relation and S_B^l the S_B relation for the event log (assuming $|S_F^l| < max$ and $|S_B^l| < max$), then the improved behavioral appropriateness metric a'_B is defined as follows:*

$$a'_B = \frac{1}{2}\left(\frac{max - |S_F^m|}{max - |S_F^l \cap S_F^m|}\right) + \frac{1}{2}\left(\frac{max - |S_B^m|}{max - |S_B^l \cap S_B^m|}\right)$$

The value $max = |L|^2 - 3|L| + 2$ has been assigned as the artificially inserted *Start* and *End* task or log event, respectively, do not allow for certain relations, and therefore a value $max = |L \times L|$ could never be reached. Note further that, building the intersection of S_F^l and S_F^m, and S_B^l and S_B^m, respectively, tuples contained in the sometimes relations of the log but not in those of the model (which can only happen if the log does not *fit* the model) are discarded and therefore the values assigned by a'_B range from 0 to 1.

Applying metric a'_B to the example yields $a'_B(M4, L1) = \frac{72-18}{72-16} \approx 0.964$. This value can be compared to $a'_B(M1, M1) = \frac{72-18}{72-17} \approx 0.982$, which is better as the process model *M1* is—due to the lack of possibility for omitting activity *G*—considered behaviorally more specific, and thus more appropriate, with respect to event log *L1* than process model *M4*. In fact, *M1* is even the best model for event log *L1* and the reason for $a'_B(M1, L1) < 1.0$ could be for instance that the log is incomplete (i.e., *H* has never been followed by *D* although this would be possible).

However, the strength of the presented approach lies in its weak notion of completeness, which, e.g., allows to recognize concurrent behavior even if not all possible interleavings of parallel tasks are represented in the log. As an example, *L2* is complete (and thus $a'_B(M4, L2)$ yields 1.0) although the possible trace *ACGHDFA* is not present either.

3.7 Final Evaluation

Having defined two alternative appropriateness metrics a'_S and a'_B they can now be used to find out which of the models is most suitable in representing the process recorded in each event log. Based on a'_S and a'_B a new unified appropriateness metric is defined and the results in Table 3.2 are enhanced by the values of these three new metrics. Again, only those combinations having a

fitness value $f = 1.0$ are compared with respect to their appropriateness measures, and therefore event log *L3* is discarded together with the model *M1* for event log *L2* (i.e., there is no unified appropriateness value given for them).

Metric 7 (Improved Appropriateness) *Based on the improved structural appropriateness metric a'_S and the improved behavioral appropriateness metric a'_B the improved unified appropriateness metric a' is defined as follows:*

$$a' = a'_S \cdot a'_B$$

Table 3.2 shows that the unified metric a' successfully picks the expected process models for both event log *L1* and event log *L2*. However, this is not necessarily the case as the behavioral and the structural dimension of appropriateness are not comparable by definition. This means that an improvement by 0.2 in structural appropriateness does not need to be perceived the same as an improvement of the same amount in behavioral appropriateness, since they measure something completely different. But no matter how they are combined (e.g., in unequal shares to emphasize one dimension more than the other), the important point is that they perform well as an indicator for structural or behavioral appropriateness on its own. This is true for a'_B and a'_S and the improvements with respect to their counterparts a_B and a_S are evaluated in the following, revising the requirements imposed in Section 2.1 for all the five metrics defined in this paper.

1. *Validity* All the metric definitions were justified by a motivation, and therefore are considered being valid.

2. *Stability* The fitness measure f is considered to be stable. Regarding the appropriateness metrics the requirement was to measure one dimension (i.e., behavioral or structural appropriateness) independently of the other. This has not been accomplished for a_B nor for a_S but for the improved metrics a'_B and a'_S:

   One can observe that—in contrast to a_B—the a'_B values for the process models *M3*, *M4*, and *M5* are equal for each of the three logs. They produce the same "footprint" (i.e., S_F and S_B relations) as they, although having a very different graph structure, allow for the same[2] behavior. This demonstrates that the improved behavioral appropriateness metric a'_B is indeed independent from structural properties of the process model.

   In contrast to a_S the metric a'_S evaluates structural properties independently from the behavior described by the model, which is proved true comparing two models not violating any design guideline but allowing for different behavior (such as $a'_S(M4) = a'_S(M6) = 1.0$).

3. *Analyzability* In contrast to a_B and a_S, possible values for both a'_B and a'_S really range from 0.0 to 1.0. Therefore, on the one hand an optimal value is defined (i.e.,1). This is

[2] In fact this corresponds to a weaker form of (trace) equivalence, which does not require *every* interleaving of parallel tasks being present but for two parallel tasks x and y includes the elements (x, y) and (y, x) in the relations S_F and S_B as soon as x (eventually) follows y and y (eventually) follows x each in at least one trace.

Table 3.2: Updated diagnostic results

	M1	*M2*	*M3*	*M4*	*M5*	*M6*
	$f = 1.0$	$f = 1.0$	$f = 1.0$	$f = 1.0$	$f = 1.0$	$f = 1.0$
	$a_S = 0.5263$	$a_S = 0.7692$	$a_S = 0.1695$	$a_S = 0.5$	$a_S = 0.4348$	$a_S = 0.5556$
	$a_B = 0.9740$	$a_B = 0.0$	$a_B = 0.9739$	$a_B = 0.9718$	$a_B = 0.9749$	$a_B = 0.9703$
L1	$a = 0.5126$	$a = 0.0$	$a = 0.1651$	$a = 0.4859$	$a = 0.4239$	$a = 0.5391$
	$a'_S = 1.0$	$a'_S = 1.0$	$a'_S = 0.0323$	$a'_S = 1.0$	$a'_S = 0.7273$	$a'_S = 1.0$
	$a'_B = 0.9818$	$a'_B = 0.0$	$a'_B = 0.9636$	$a'_B = 0.9636$	$a'_B = 0.9636$	$a'_B = 0.9455$
	$a' = 0.9818$	$a' = 0.0$	$a' = 0.0311$	$a' = 0.9636$	$a' = 0.7008$	$a' = 0.9455$
	$f = 0.9952$	$f = 1.0$	$f = 1.0$	$f = 1.0$	$f = 1.0$	$f = 1.0$
	$a_S = 0.5263$	$a_S = 0.7692$	$a_S = 0.1695$	$a_S = 0.5$	$a_S = 0.4348$	$a_S = 0.5556$
	$a_B = 0.9705$	$a_B = 0.0$	$a_B = 0.9745$	$a_B = 0.9669$	$a_B = 0.9706$	$a_B = 0.9637$
L2		$a = 0.0$	$a = 0.1652$	$a = 0.4835$	$a = 0.4220$	$a = 0.5354$
	$a'_S = 1.0$	$a'_S = 1.0$	$a'_S = 0.0323$	$a'_S = 1.0$	$a'_S = 0.7273$	$a'_S = 1.0$
	$a'_B = 1.0$	$a'_B = 0.0$	$a'_B = 1.0$	$a'_B = 1.0$	$a'_B = 1.0$	$a'_B = 0.9811$
		$a' = 0.0$	$a' = 0.0323$	$a' = 1.0$	$a' = 0.7273$	$a' = 0.9811$
	$f = 0.5397$	$f = 1.0$	$f = 0.4947$	$f = 0.6003$	$f = 0.6119$	$f = 0.5830$
	$a_S = 0.5263$	$a_S = 0.7692$	$a_S = 0.1695$	$a_S = 0.5$	$a_S = 0.4348$	$a_S = 0.5556$
L3	$a_B = 0.8909$	$a_B = 0.0$	$a_B = 0.8798$	$a_B = 0.8904$	$a_B = 0.9026$	$a_B = 0.8894$
	$a'_S = 1.0$	$a'_S = 1.0$	$a'_S = 0.0323$	$a'_S = 1.0$	$a'_S = 0.7273$	$a'_S = 1.0$
	$a'_B = 0.9231$	$a'_B = 0.0$	$a'_B = 0.9138$	$a'_B = 0.9138$	$a'_B = 0.9138$	$a'_B = 0.8966$

especially important as a stop condition in the context of an iterative approach looking for appropriate process models, such as genetic mining [28], but also for a human analyst as it indicates that there is no better solution available. On the other hand the existence of a Rational Zero (i.e., 0) enables propositions like, e.g., "Model A is twice as structurally appropriate as model B" [27]. However, an in-depth scale type discussion of the presented metrics is out of the scope of this paper.

The metric f also defines an optimal value, i.e., if a log can be perfectly replayed, the measured value is 1.

4. *Reproducibility* For the metrics f and a_B there is an issue with respect to the reproducibility requirement, which is related to a potentially non-deterministic log replay on a logical level (see also Section 4.4). The other metrics are completely reproducible.

5. *Localizability* Like for f it has been shown that, in contrast to a_B and a_S, potential points of improvement can also be localized for both a'_B and a'_S. This is crucial as otherwise it is not possible to gain more insight into a problem and to, e.g., decide on potential alignment actions.

4 Implementation

The main concepts discussed in the previous section have been implemented in a plug-in for the ProM framework. The conformance checker replays an event log within a Petri net model in a non-blocking way while gathering diagnostic information that can be accessed afterwards. It calculates the token-based fitness metric f, taking into account the number of process instances represented by each logical log trace, the structural appropriateness a_S, and the behavioral appropriateness a_B. Furthermore, the diagnostic results can be visualized both from a log-based and model-based perspective.

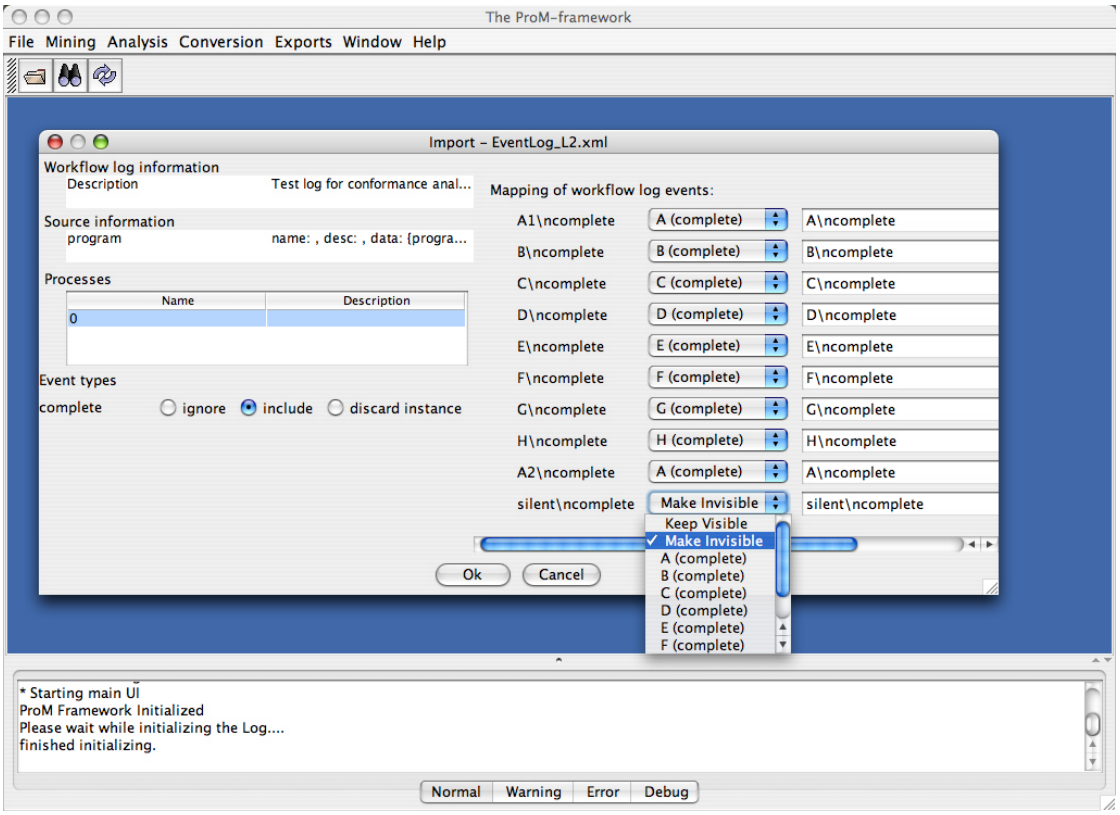


Figure 4.1: Screenshot while associating model tasks with log events

During log replay the plug-in takes care of invisible tasks that might enable the transition to be replayed next, and it is able to deal with duplicate tasks (see also Section 4.3). Figure 4.1 shows a screenshot of the ProM framework establishing the mapping between process model *M4* and event log *L2*. While the left column lists all the different transitions contained in the Petri net model each one of them can either be related to a log event contained in the associated

log, or made invisible (i.e., the task is not related to any log event). A third possibility is to keep it visible (i.e., the task has a log event associated but it is not present in this log). The model tasks *B complete* to *H complete* are all one-to-one mapped onto a log event with the same name, respectively, while *A1 complete* and *A2 complete* are both related to the same log event *A complete*, i.e., they are duplicate tasks. What is more, the task *silent complete* is made invisible. Note that the simplifying assumption of denoting the mapping by means of a common label (Section 2.3) is removed for practical use. Since the mapping is made explicit any task label can be set in the right column (i.e., either the name of the task, or the name of the log event, or even something else).

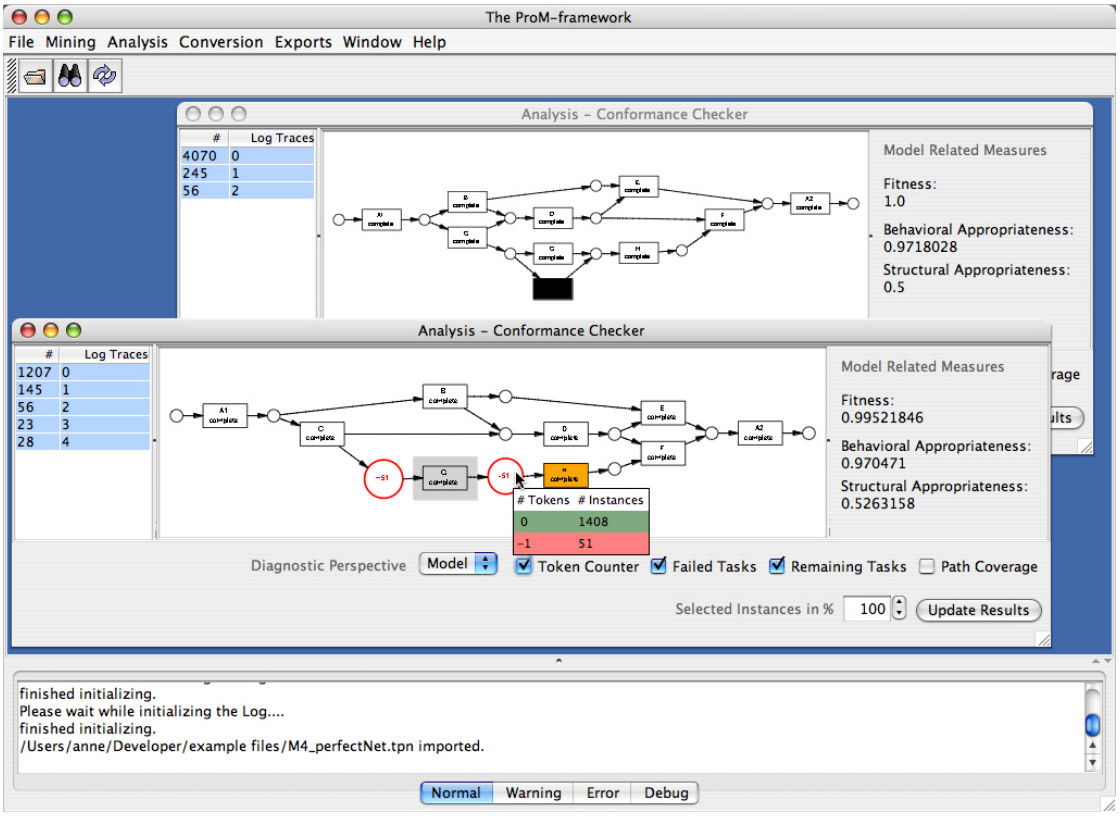


Figure 4.2: Screenshot of the conformance analysis plug-in

The lower part of Figure 4.2 shows the result screen of analyzing the conformance of event log *L2* and process model *M1*. As discussed before, for replaying *L2 M1* lacks the possibility to skip activity *G*, which also becomes clear in the visualization of the model augmented with diagnostic information. In contrast to Figure 3.7, which depicts the amount of missing and remaining tokens from a replay perspective, here the number of process instances per trace is taken into account. Thus, instead of indicating one token missing and remaining for both log trace 3 and 4 in total there are $23 + 28 = 51$, each missing and remaining. Hovering over such a marked place or transition provides more detailed information, e.g., about the number of instances leaving or lacking a certain amount of tokens at that place.

In the other conformance analysis window event log *L1* is measured to fit with process model *M4* and the calculated values for structural and behavioral appropriateness (a_S and a_B) are in line with the results determined in Section 3.4.

The remainder of this section documents the implementation work by first giving an overview of the framework concepts in Section 4.1, then describing the architecture of the plugin implemented in Section 4.2, and modeling two important algorithms needed for log replay in Section 4.3. Finally, the implemented techniques are evaluated and requirements towards future implementation work will be discussed in Section 4.4.

4.1 The ProM Framework

The ProM framework is meant to ease the implementation of new algorithms or techniques in the field of process mining, e.g., for testing purposes or to share them with others. This is accomplished by allowing new functionality to be implemented outside of the framework, i.e., treating it like a black box with a well defined interface, and to be *plugged in* independently. Interoperability is ensured in conjunction with the ProMimport framework[1], which converts logs from existing (commercial) PAIS to the XML format that ProM uses as log input. Furthermore, the ProM framework provides high-level access to, e.g., log files or graph structures like Petri nets to the programmer.

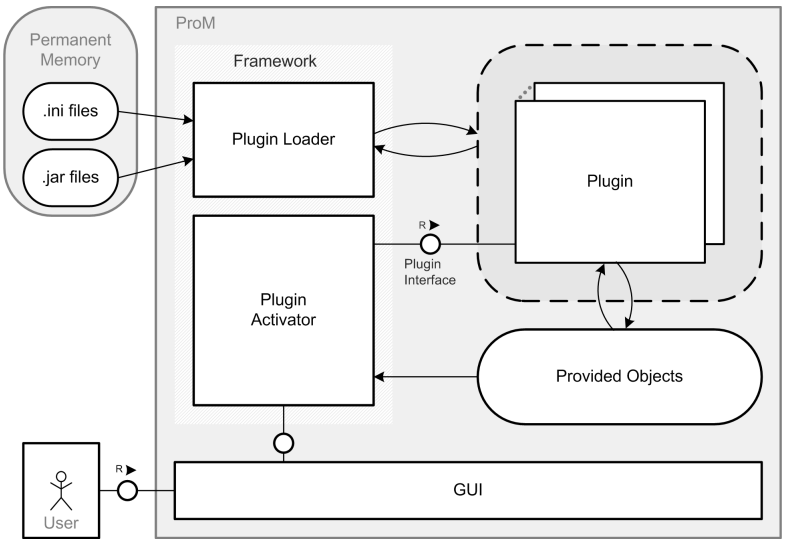


Figure 4.3: Loading plug-ins into the ProM framework

The general concept of loading plug-ins during tool start-up has been illustrated in Figure 4.3 with the help of a FMC[2] *block diagram*. In a block diagram there are active system components called agents (rectangular shape) and passive system components called locations (rounded

[1]The software can be downloaded from *http://www.processmining.org*.

[2]Fundamental Modeling concepts (FMC) is a modeling notation consisting of *Block diagrams* to describe compo-

shape), whereas a location is either a storage or a channel (depicted by a smaller circle). Agents communicate with each other via channels or shared storages.

In order to add a new plug-in (cf. Figure 4.3) the corresponding .jar archive must be added to the /lib/plugins folder and it needs to be registered with the respective .ini file. Note that this does not require any intervention in the ProM application, thus ensuring compatibility with other plug-ins. During tool start-up all the registered plug-ins are loaded, which means that they are made available as an active component within the ProM application. This creation process is depicted as a structure variance, i.e., the compositional structure has been modified by creating active plug-in components from a passive location. From that point in time on the framework component is able to communicate with the plug-ins and can activate them in the right context.

Every plug-in needs to implement the *Plugin interface*[3], which among others specifies the required input items (if any) that are needed for using the plugin. Moreover, a plug-in may export *Provided objects*, which are used by the framework to dynamically show all those plugins to the user that are able to do something with at least one of them. This way the framework makes sure that a plug-in is only invoked if all the necessary input items, i.e., provided objects, are available.

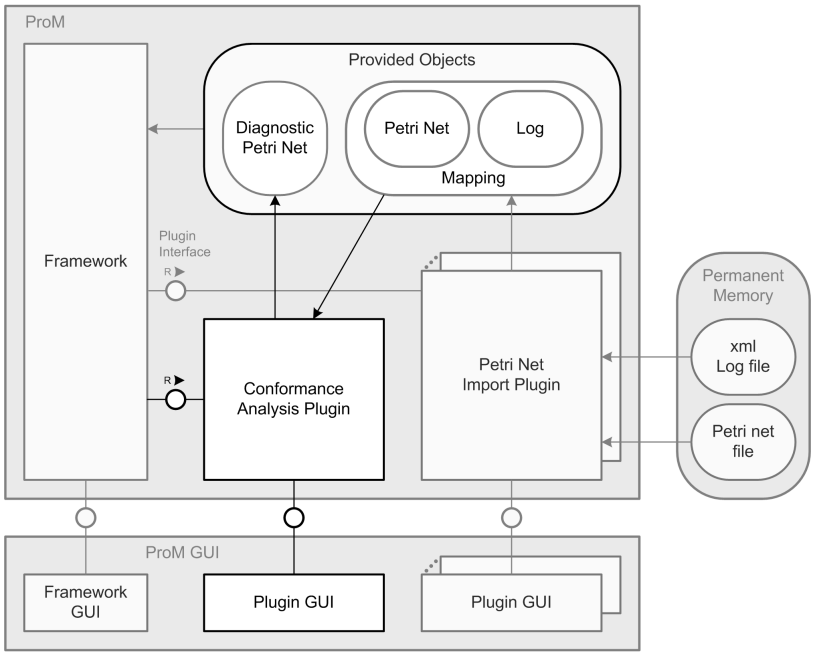


Figure 4.4: Invoking the conformance analysis plug-in

Consider Figure 4.4 as an example situation in which the *Petri net import plugin* was used to open a Petri net file and associate it with a given log file (i.e., a mapping of model tasks and log

sitional structures, *Petri nets* to depict dynamic structures, and *Entity relationship diagrams* to visualize value range structures of software(-intense) systems [23]. More information and MSVisio stencils can be downloaded from *http://www.f-m-c.org/*.

[3]The *R* stands for *Request/response channel*, which is an abbreviated notation for drawing two directed—request and response—channels indicating the initiating direction of communication (refer to *http://www.f-m-c.org/* for further information).

events has been established). It offers this Petri net and log representation as a provided object which can be used by the *Conformance analysis plugin*. Therefore, the conformance checker appears in the "Analysis" menu of the ProM tool and the user may invoke it. Based on the given Petri net and its associated log the analysis can be performed and the results in turn are provided to the framework, e.g., as a diagnostic visualization of the Petri net model for graphical export.

What is more, every plug-in provides its own *Graphical user interface* (GUI), which is automatically integrated in the GUI of the ProM application.

4.2 The Conformance Analysis Plug-in

Figure 4.5 shows the conformance analysis plug-in in a refined manner. Semantically, there are three main components responsible for replaying the log, calculating the metrics, and visualizing the results, respectively. Therefore, the plug-in maintains some diagnostic data structures within its internal memory which are filled by the *Conformance checker* while replaying the log (note the directed edge indicating write access to the *Results* storage) and accessed afterwards to calculate a metric or to create a visualization (note the directed edge indicating read access by the *Visualizer* and the *Metrics calculator*).

The user interacts with the plugin via its graphical user interface, e.g., invoking the analysis or changing the type of visualization.

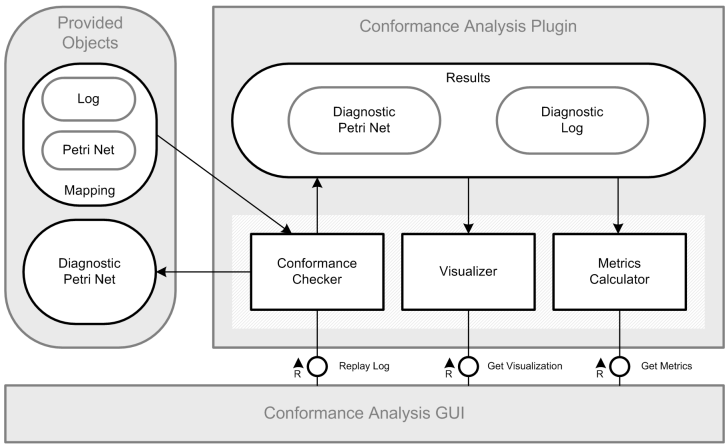


Figure 4.5: Architecture of the conformance analysis plug-in

Figure 4.6 shows the implementation structure of the conformance analysis plug-in using a UML 2.0[4] *class diagram*. It depicts the java classes with their most important attributes and methods, and the relationships between them. The classes located in the upper part of the figure belong to the ProM framework while the lower classes are newly implemented by the conformance analysis plug-in.

[4]Unified Modeling Language (UML) 2.0 is a modeling notation defining twelve types of diagrams to describe *structural*, *behavioral*, and *model managing* aspects of software systems [31]. Further information can be obtained from *http://www.uml.org/*.

As indicated before the plugin interface must be implemented for enabling communication with the framework component. For analysis plug-ins there is an `AnalysisPlugin` interface which requires four methods specifying the name of the plug-in, the user documentation as a HTML[5] fragment, the required input items, and the `analyse()` method to be called as soon as the plug-in is invoked. The result is returned to the framework as a GUI component (note that `ConformanceAnalysisGUI` is derived from `JPanel`), which is then displayed in a separate window component. Furthermore, it implements the `Provider` interface to export a diagnostic visualization of the analysis results. The log replay is carried out by calling the `replayLogInPetriNet()` method of the `ConformanceChecker` and the results are obtained as a `ConformanceCheckResult` object, which provides access to to the diagnostic data that has been collected.

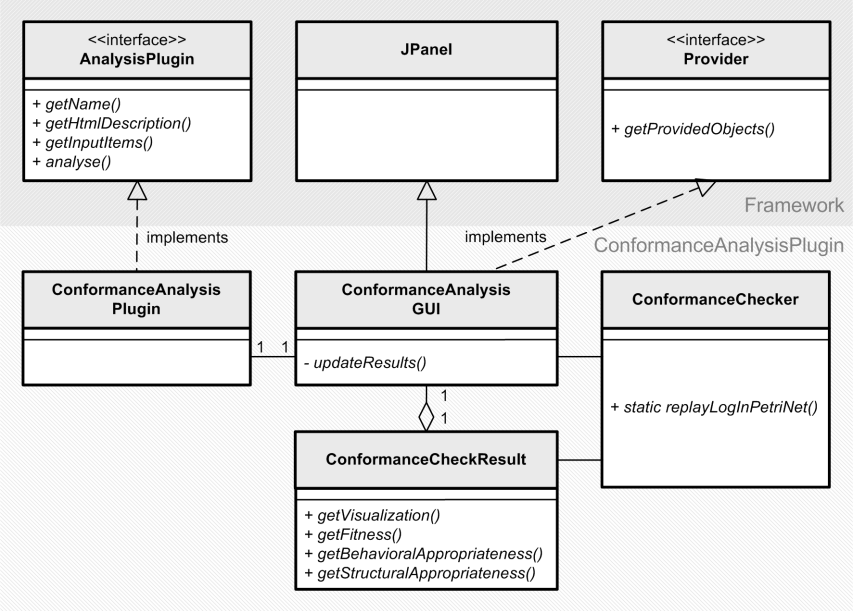


Figure 4.6: Class diagram of the plug-in implementation

Figure 4.7 shows another class diagram also containing the class `ConformanceCheckResult` that can be seen as a link between the two pictures. Note that with respect to Figure 4.5 the view has changed from a semantic perspective to an implementation-specific one. Due to the object oriented paradigm data and functionality are closely integrated, i.e., instead of active components (*ConformanceChecker*, *Visualizer*, *MetricsCalculator*) working on data (the *Results* storage) the diagnostic data structure is built as a network of interacting objects, each serving a well-defined purpose.

A `ConformanceCheckResult` maintains an object each of the class `DiagnosticPetriNet` and the class `DiagnosticLogReader`, which both respectively extend the classes `PetriNet` and `LogReader` provided by the ProM framework. Most of the classes within the plug-in reuse

[5]HyperText Markup Language (HTML) is a document format specification standardized by the World Wide Web Consortium (W3C). The specification can be obtained from *http://www.w3.org/*.

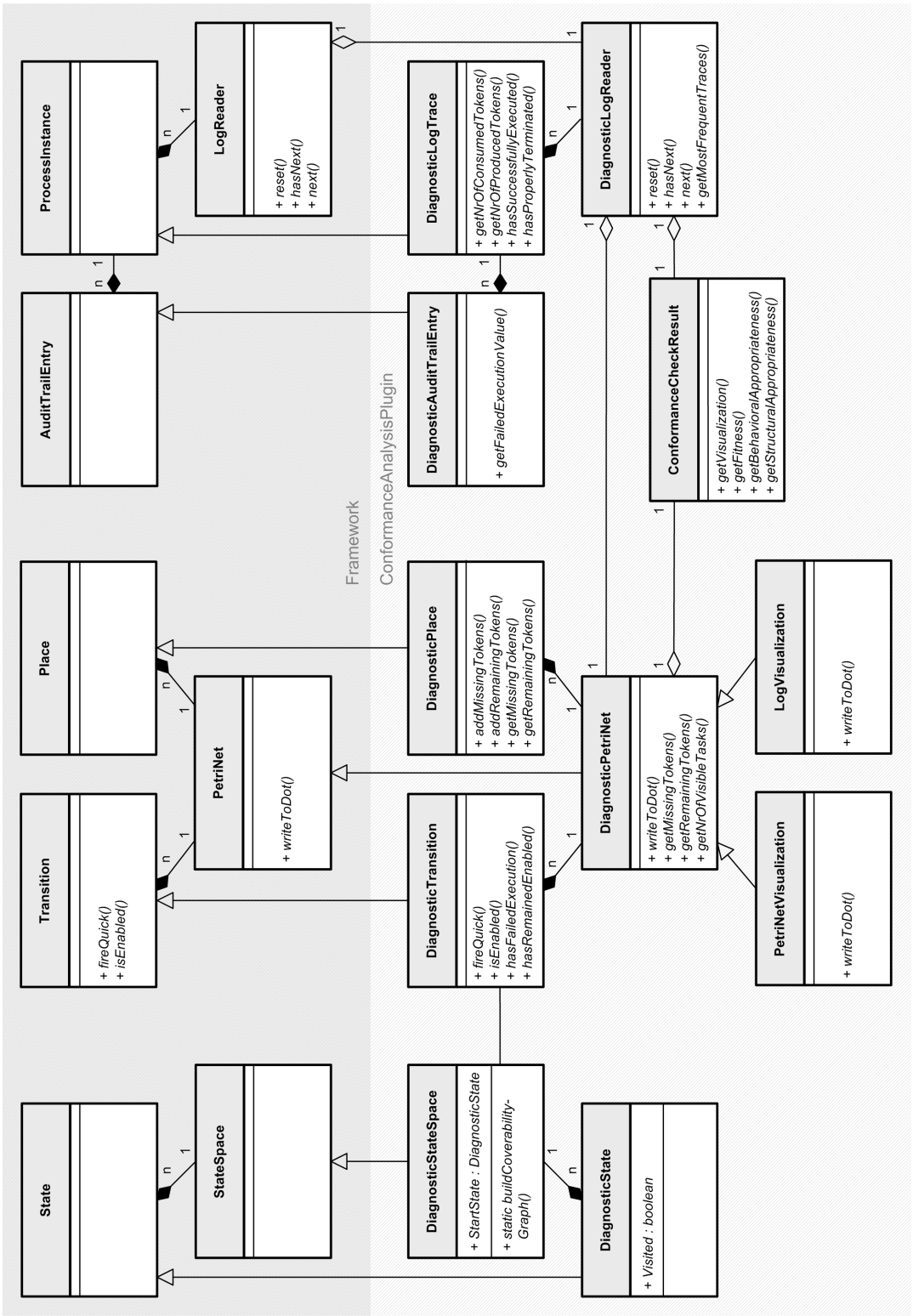


Figure 4.7: Class diagram of the diagnostic data structure

functionality inherited from the framework while enhancing it with the diagnostic data collected. As an example the class `DiagnosticTransition` overrides `isEnabled()` inherited from the class `Transition` to fire the shortest sequence of invisible tasks enabling the transition in question, if possible. To this end a partial exploration of the state space (i.e., the coverability graph provided by the class `DiagnosticStateSpace`) based on the current marking of the net is necessary. While firing a `DiagnosticTransition` the number of consumed and produced tokens is recorded, and if there are tokens missing or remaining after log replay this is recorded in the respective `DiagnosticPlace`.

For the visualization of diagnostic data the plug-in re-uses the Dot[6] mechanism applied by the framework. Predefined methods like `writeToDot()` can be overridden to enhance the default implementation of the `PetriNet` class by diagnostic information or to even change the view to, e.g., the log perspective.

4.3 Log Replay Involving Invisible and Duplicate Tasks

When performing such a non-blocking log replay involving invisible and duplicate tasks, situations in the run of replay may be encountered where the state space of the process model needs to be partly explored. This is the case for the solution of two non-trivial problems described in the following, namely whether a specific task can be enabled via firing a sequence of invisible tasks (see Section 4.3.1) and the decision for one task among duplicates (see Section 4.3.2).

To provide a link between the general problem solution and its implementation, Figures 4.8 and 4.9 visualize the algorithms in a rather abstract way as a Petri net in FMC notation (which was chosen as it defines a standard way to model recursion[7]) while following the implementation structure and indicating the names of the methods implemented.

4.3.1 Enabling a Task via Invisible Tasks

The first algorithm deals with the fact that invisible tasks are considered lazy, i.e., they might fire in order to enable one of their succeeding visible tasks (recall that invisible tasks will never be fired directly in the flow of log replay since they do not have a log event associated). This implies that in the case that the task currently replayed is not directly enabled, it must be checked whether it can be enabled by a sequence of invisible tasks before considering it having failed. The conflict between multiple enabling sequences is solved by choosing an arbitrary element out of the set of shortest sequences. This aims at having minimal possible side effects on the current marking of the net, e.g., not to unnecessarily fire an invisible task that is in conflict with another task later to be replayed. Figure 4.8 shows the flow of the method `isEnabled()` implemented in `DiagnosticTransition`, which has been overridden to replace the default behavior of `Transition` in the following way.

Since a diagnostic transition can also be enabled "through" one or multiple invisible tasks, a `list` is created to capture this (potential) enabling sequence. If the transition is enabled

[6] Open source graph layout software used by the ProM framework for visualizing graph structures like, e.g., Petri nets or state spaces. Further information can be obtained from *http://www.graphviz.org/*.

[7] For the general recursion scheme and further examples refer to *http://www.f-m-c.org/*.

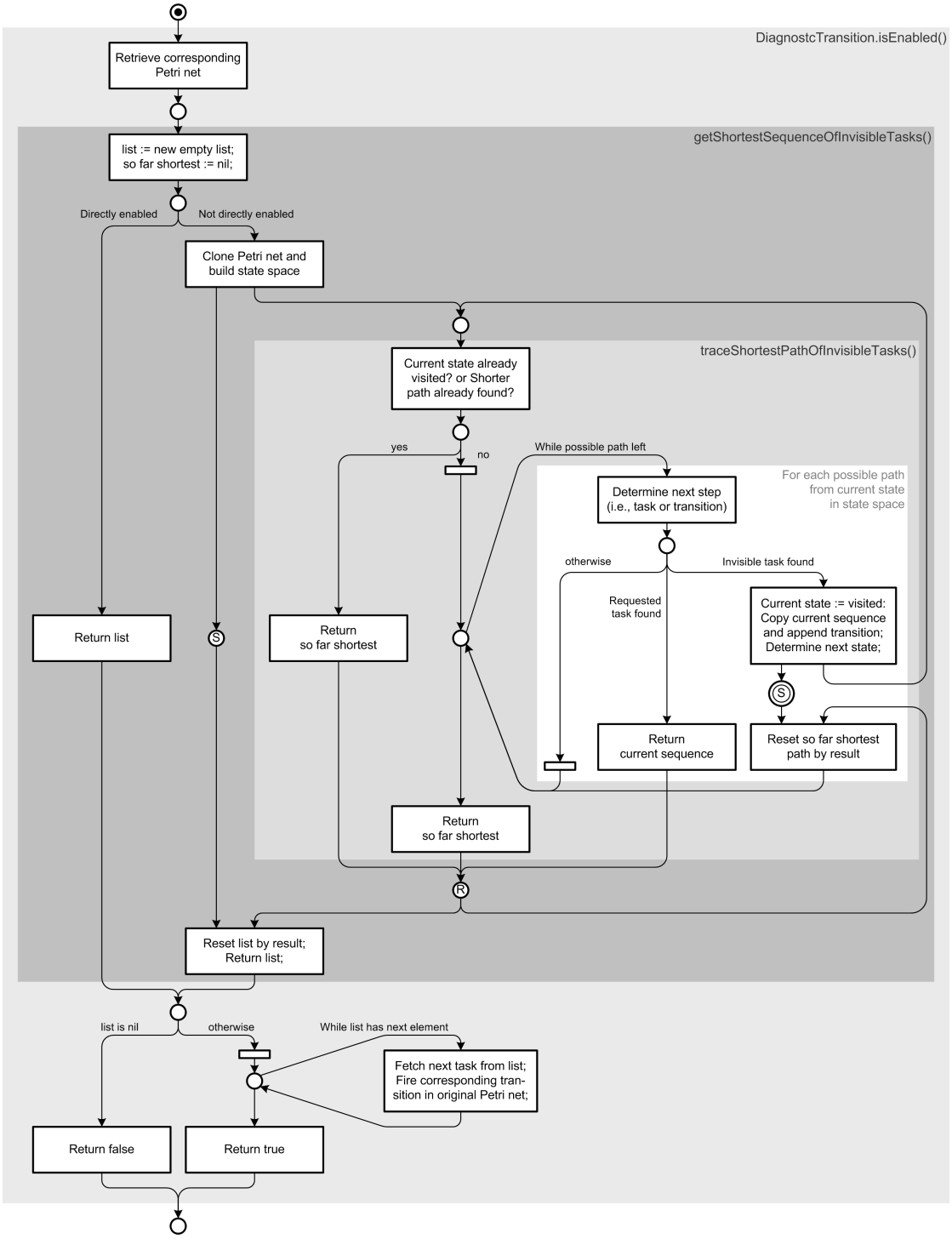


Figure 4.8: Recursive algorithm for transparently enabling a replayed task through a sequence of invisible tasks (if possible)

anyway, this sequence remains empty and the method returns **`true`**. Note that an empty list has length 0 but is not `nil` (which could be seen as *undefined*). In the case of not being directly enabled the state space is built from the current marking of the Petri net. To prevent nets that accumulate tokens from producing an infinite state space (which could happen, e.g., building the reachability graph of a Petri net) the coverability graph builder of the ProM framework has been used for implementation. In a coverability graph a so-called ω-state denotes an extended marking, which subsumes all the different finite markings that result from token accumulation in an infinite marking [30, 33].

Then `traceShortestPathOfInvisibleTasks()`—the recursive program part—is called. Its input place is the *entry point* of the recursion, which means that initially called by the enclosing program part it can then be called several times from the recursive part itself. At the same time a token is put in the *stack place* (S) for guiding the recursion handling. Stack places are always input places for transitions that additionally have a *return place* (R) as input. All the stack places together constitute the return stack, which is used to store information about return positions. When the return place gets marked and more than one associated stack places have a stack token the conflict is always solved in the same manner: the newest token on the stack must be consumed first. The newest token belongs to exactly one stack place and so the transition where this stack place is an input place will fire.

Entering the recursive program part the idea is to trace each possible path of invisible tasks in the state space until one of the following end-conditions is reached:

(a) If the current state was already visited during traversal, it means that the state space is cyclic and recursion stops to prevent an infinite loop.

(b) If a shorter sequence of invisible tasks enabling the transition in question than the one currently traced has already been found, it is not necessary to pursue this route any further.

Assuming that neither (a) nor (b) are fulfilled all possible paths from the current state in the state space are considered and further traced as long as the next step is still an invisible task. If this is the case the current state is marked as being visited already, the invisible task encountered is appended to the currently pursued sequence, and passing the corresponding successor state `traceShortestPathOfInvisibleTasks()` is called recursively. At the same time a token is put in the stack place[8] to continue handling this path after the procedure returns. Since the time stamp[9] of this token is more recent than the one of the token in the stack place of the enclosing program part, the conflict is always solved in favor of the transition in the recursive part. Only if there is no token left in this multi-token stack place, i.e., the recursion is completely handled, the procedure will return to `getShortestSequenceOfInvisibleTasks()`.

On a logical level, there are two more end-conditions that can be reached evaluating all possible future steps based on the current traversal state:

(c) If the transition to be replayed is encountered, a possible enabling sequence has been found and will be returned.

[8] Enlarged places such as this stack place can hold multiple tokens at the same time. The amount can be limited and annotated at the place while a double circle denotes an infinite capacity.

[9] Here a notion similar to Colored Petri Nets (CPN) [25] has been used, i.e., the possibility to assign a token different values such as a time stamp.

(d) If no invisible task can be found, recursion aborts as the path cannot be followed any further.

Following the flow of the algorithm to its end it must be kept in mind that the place holder for the best sequence, referred to as the `so far shortest`, remains `nil` until the requested transition was encountered at least once while tracing those paths of invisible tasks in the state space. If no possible sequence could be found, i.e., the checked diagnostic transition cannot be enabled via firing any invisible tasks either, the `list` will be set to `nil` and the method returns **`false`**. However, in the case a possible path *has* been found, the gained sequence of invisible tasks is executed to transparently enable the diagnostic transition and the method returns **`true`**.

4.3.2 Choosing a Duplicate Task

The second algorithm deals with the fact that the mapping between model tasks and log events (see also Section 2.3) may result in duplicate tasks. During log replay this is a problem since encountering a log event being associated with multiple tasks in the model it is not always clear which of the duplicates should be executed. The overall goal will be to replay a log correctly, if possible. Figure 4.9 shows the flow of the solution implemented by the method `chooseEnabledDuplicateTask()`, which is called by `replayTrace()` in the case of finding more than one transition associated with the log event currently replayed.

At first, only those tasks being enabled[10] by the current marking of the Petri net are selected. If there is none enabled the method returns immediately and the `ConformanceChecker` will fire an arbitrary task from the list of duplicates (since correct replay is not possible anyway). If there is exactly one task enabled it is returned and will be executed subsequently. This will often be the case in scenarios where the same task is carried out in multiple contexts (such as setting a checkpoint at the begin and at the end of a the example process in Figure 3.1), i.e., the marking of the net clearly indicates which choice is best. However, if there are more candidates enabled the remaining log events must be considered to determine the best choice. For these purposes, `chooseBestCandidate()` is called, making a copy of the current replay scenario for each enabled duplicate and firing the transition belonging to that candidate (i.e., starting to play over every case). Then the *entry point* for the recursive method tracking these scenarios, i.e., `traceBestCandidate()`, is reached and will not return until there is only one scenario left, which can then be reported to the initial caller in order to proceed with the actual log replay.

Entering the recursive program part at first the following end-condition is checked:

(a) If there are no log events left in the trace currently being replayed, one of the remaining candidates is chosen arbitrarily and recursion is finished.

Assuming that (a) is not fulfilled the next log event is fetched from the trace and the number of associated transitions is determined. If there is only one task associated to it, those scenarios are kept and updated where this task is enabled, i.e., where the next replay step can be executed successfully as well. If there are multiple tasks associated, the best duplicate must also be chosen

[10] Note that in the context of this algorithm the possibility of invisible tasks indirectly enabling other transitions needs to be respected again (but without actually changing the marking of the replayed net). However, from now on it is abstracted from this issue.

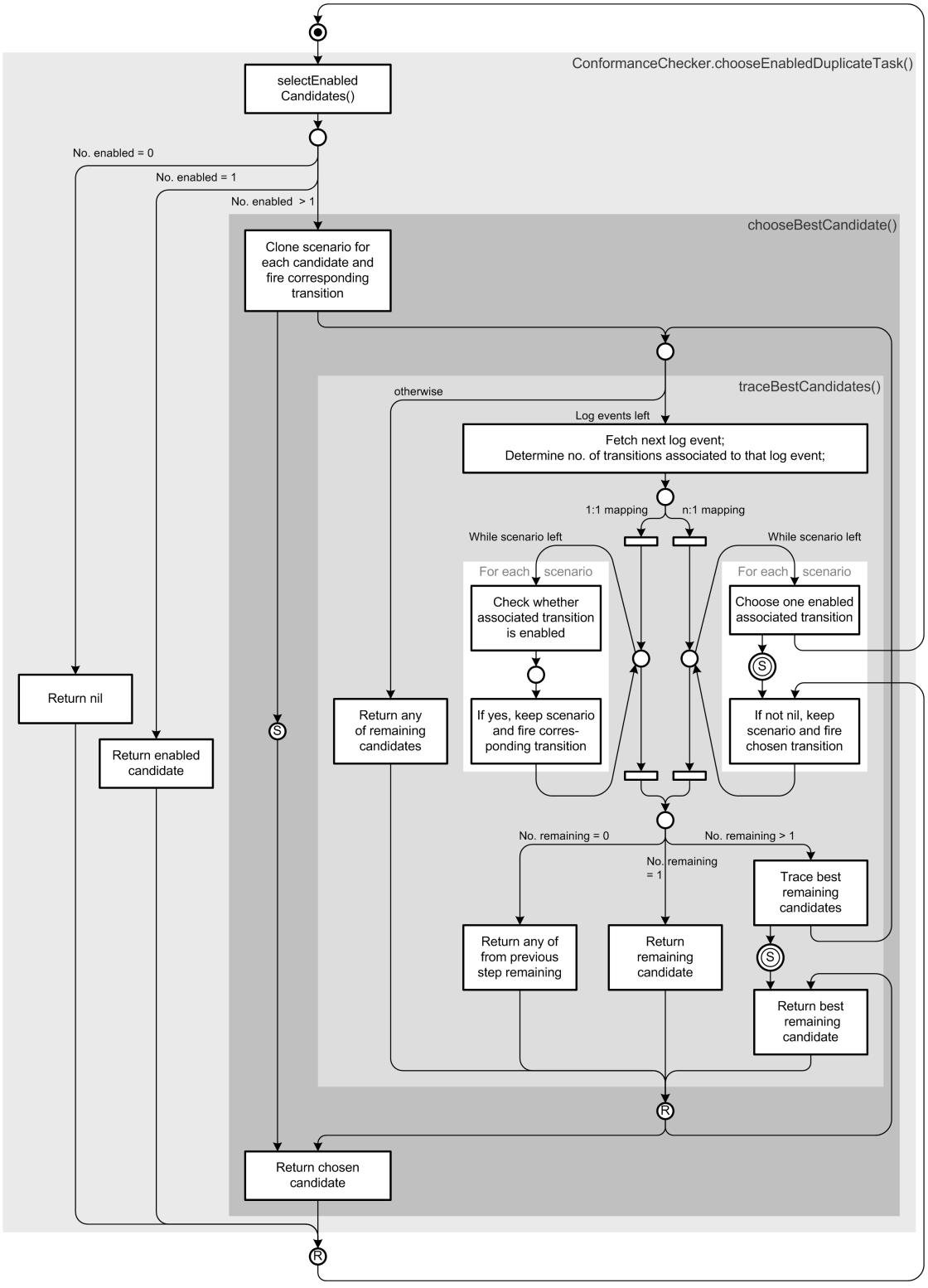


Figure 4.9: Recursive algorithm for choosing a duplicate task during log replay

for this case and for each scenario, realized by a recursive call to the very entry point of the whole procedure. Note that the enclosing program part belonging to *this* recursive call, which is `replayTrace()`, is not contained in the picture. Then, similarly, those scenarios are kept and updated that were able to determine an enabled duplicate task for this anticipated next replay step. The possibility for having a 0:1 mapping has been discarded since the log is—according to Section 2.3—assumed to be pre-processed, i.e., log events not associated to any task in the model were removed during import.

Now, the number of remaining scenarios is checked and if there are more than one left recursion proceeds to check at least one step further. Otherwise one of the two following end-conditions is reached, stopping the recursion:

(b) If only one candidate remains, this one is returned as the best choice.

(c) If, after replaying this next log event, none of the scenarios is left, any of the previously kept candidates is returned.

4.4 Assessment and Future Implementation Work

Regarding the algorithms presented in the last section, it is important to be aware of the fact that, e.g., choosing any duplicate task in the case of none of them being enabled in the first place, might render a log replay non-deterministic on a logical level. This does not mean that analyzing the same two files (containing the model and the log, respectively) might become non-deterministic, it will always yield identical results. However, this is not necessarily the case as soon as the Petri net file is exchanged by another one, still defining the same Petri net (i.e., on a logical level) but syntactically specifying the transitions in a different order. This leads to a differently ordered list held internally after import, which in the case of choosing any non-enabled duplicate task might then lead to firing another transition, possibly leaving more tokens in the net and thus affecting the metrics f and a_B.

On this semantic level a fully deterministic log replay involving invisible and duplicate tasks cannot be ensured by definition. But also guaranteeing equal values for the metrics calculated would dramatically increase complexity as the state space would need to be explored in a much more extensive way, comparing the amount of produced, consumed, missing, and remaining tokens, and enabled transitions for every possible scenario. So clearly there is a trade-off between full reproducibility according to Requirement 4 from Section 2.1 and performance, which can be expected to decrease considerably and therefore hinder useful application while adding very little practical value (as this semantic non-determinism will only cause f and a_B value deviations while analyzing poorly fitting logs in conjunction with models involving duplicate tasks).

However, if the log fits the model the conformance analysis plug-in is able to replay the log correctly, also while dealing with invisible and duplicate tasks. This is very important as any mismatch thus really indicates a conformance problem, which can then be quantified to assess its dimension and located to further analyze possible causes and corrective actions.

The performance of the log replay procedure as it is implemented in the conformance checker is hard to appraise. It might vary a lot, depending on how many duplicate and invisible tasks are involved as in this case the state space needs to be partially explored. But even the fact that, e.g., the state space of the model is built after each replay step for the current marking of the net to determine the number of enabled transitions (for a transition potentially being enabled through an invisible task), which is needed to calculate the metric a_B, might cause problems in the case that the state space is very large.

So it is intended to make the implementation more flexible by offering the choice for which metrics should actually be calculated. But in general the log replay approach is very promising as for models not containing any invisible or duplicate tasks the complexity is proportional to the size of the log (and does not have to deal with the issue of completeness). It would be important to verify the presented techniques with respect to real business scenarios, e.g., in the form of a case study. Therefore, the improved appropriateness metrics should also be implemented in the conformance checker.

Regarding implementation of the improved behavioral appropriateness metric a'_B one would first derive the S_F and S_B relations from the state space of the process model. This could be a bottleneck as for it the state space of the model needs to be fully explored. Then, they would be verified with respect to the log. In fact, one could aim at the falsification of both counterparts for each pair of labels contained in S_F^m and S_B^m, making use of the fact that $(x, y) \in S_F$ iff $(x, y) \notin A_F \wedge (x, y) \notin N_F$, or $(x, y) \in S_B$ iff $(x, y) \notin A_B \wedge (x, y) \notin N_B$, respectively. The cost for this part of the analysis will increase proportionally with the size of the (aggregated) log.

It would be interesting to validate the presented metric with respect to some real business processes as the global character of the approach on the one hand promises to incorporate free-choice constructs (i.e., control flow constraints that cannot be recognized from local dependencies), but on the other hand it also seems as if non-short loops dilute the footprints of their enclosed tasks in such a way that the Never relations disappear.

In general, the idea to verify certain properties for a set of log traces is related to the LTL checker [10], which has been implemented as a plug-in for the ProM framework. Linear Temporal Logic (LTL) is a field of mathematical logic that is able to talk about the future of paths. The LTL checker is able to verify a given LTL expression with respect to a given workflow log.

As far as the implementation of the improved structural appropriateness metric a'_S is concerned, alternative ways to determine the set of redundant invisible tasks I_R should be examined as the current definition requires a complete exploration of the (modified) state space for every invisible task in the model. For determining the set of alternative duplicate tasks D_A one would also need to fully explore the transition system corresponding to the process model once (which, as discussed, could cause problems for a very big state space). However, if it is possible then it can be realized together with the derivation of the relations S_F^m and S_B^m for the metric a'_B.

5 Related Work

Regarding its purpose conformance testing as presented in this paper is closely related to the work of Cook et al. [12, 11] who have introduced the concept of process validation. They propose a technique comparing the event stream coming from the process model with the event stream from the execution log (cf. Section 2) based on two different string distance metrics. To face the problem of time-complexity while exploring the state space of the model they investigate (and reject) several techniques from domains like compiler research and regular-expression matching. In the end an incremental, data-driven state-space search is suggested, using heuristics to reduce the cost. An interesting point is that they include the possibility to assign weights in order to differentiate the relative importance of specific types of events. In [11] the results are extended to include time aspects. The notion of conformance has also been discussed in the context of business alignment [1], security [4], and genetic mining [28] (all proposing some kind of replay).

However, in each of the papers mentioned only fitness is considered and appropriateness is mostly ignored.

Conformance testing assumes the presence of a given descriptive or prescriptive process model, and therefore has a different starting point, but nevertheless it is closely related to process mining [7, 6], which aims at the discovery of a process model based on some event log. In the desire to derive a "good" model for the behavior observed in the execution log, shared notions of fitness, behavioral appropriateness and structural appropriateness can be recognized.

In [20] the process mining problem is faced with the aim of deriving a model which is as compliant as possible with the log data, accounting for fitness (called completeness) and also behavioral appropriateness (called soundness). Starting with a disjunctive workflow schema containing all the traces from the log (cf. Figure 3.4) they try to incrementally cluster these traces until a given lower bound for the number of schemata contained is reached, which, in fact, corresponds to some notion of structural appropriateness as well.

Another example is the process mining approach presented in [34], which is aiming at the discovery of a WF-net that (i) potentially generates all event sequences appearing in the execution log (i.e., fitness), (ii) generates as few event sequences not contained in the execution log as possible (i.e., behavioral appropriateness), and (iii) captures concurrent behavior and (iv) is as simple and compact as possible (i.e., structural appropriateness).

Moreover, techniques such as considering some form of causal relation can be borrowed from the process mining research, just as insights gained into concepts like correctness, completeness, and noise are also relevant in the context of conformance testing.

Both process mining and conformance testing can be seen in the broader context of Business (Process) Intelligence (BPI) and Business Activity Monitoring (BAM). Tools, as described in [21, 29, 22], however, often focus on performance measurements rather than monitoring

(un)desirable behavior.

6 Conclusion

From the coexistence of explicit process models and event logs originates the interesting question "Do the model and the log *conform* to each other?". This question is highly relevant as their diversion is expected, yet indicates a clearly undesirable inconsistent state.

This paper proposes an incremental approach to check the conformance of a process model and an event log. At first, the *fitness* between the log and the model needs to be ensured (i.e., "Does the observed process comply with the control flow specified by the process model?"). At second, the *appropriateness* of the model can be analyzed with respect to the log (i.e., "Does the model describe the observed process in a suitable way?"). During this second phase two aspects of appropriateness are considered, evaluating *structural* properties of the process model on the one hand ("Is the behavior specified by the model represented in a structurally suitable way?") and *behavioral* properties on the other ("Does the model specify the behavior of the observed process in a sufficiently specific way?").

One metric (f) has been defined to address fitness and two metrics each approach structural appropriateness (a_S and a'_S) and behavioral appropriateness (a_B and a'_B). Together they allow for the quantification of conformance, whereas fitness should be ensured before appropriateness is analyzed. However, since in real life business scenarios a fitness of 100% is unlikely, it would be interesting to investigate until which degree of fitness the behavioral appropriateness analysis can still produce useful results, or to even explicitly develop a behavioral appropriateness technique that is able to deal with noise. Furthermore, as shown in this paper behavioral appropriateness requires some notion of completeness by definition. Structural appropriateness, in contrast, can even be evaluated independently of the logged data at all as only the suitability of the model in representing the specified behavior is appraised. To ensure the usefulness of the metrics defined three requirements were formulated, calling for their (1) validity, (2) stability, and (3) reproducibility. A violation of the second requirement has led to the development of the two alternative appropriateness metrics a'_S and a'_B, which—in contrast to their counterparts a_S and a_B—are able to measure only one dimension of appropriateness, independently of the other.

Besides the quantification of fitness and appropriateness, it is crucial to assist the analyst in finding the location of a conformance problem. It has been shown that the approaches presented for the formation of f, a'_S, and a'_B *are* able to locate the respective problem areas in the model or the log.

So the presented techniques constitute a powerful means to indicate a conformance problem and to estimate its dimension, while providing the user with some visual feedback pinpointing those parts that should be revised.

Future work will aim at the implementation of the alternative appropriateness approaches a'_B and a'_S in the first place, to enable the application of all the presented techniques in real business scenarios, and for the appraisal of the metrics themselves (with respect to performance and effectiveness). To really support the incremental character of the presented approach it would

be nice if one could—following the suggestions of the conformance analysis tool—simulate adjustments in both the model and the log in order to, e.g., proceed with the analysis of another conformance aspect.

Naturally, additional information about both the application context and the technology used can be exploited to extend and/or customize the conformance analysis techniques presented in this paper. As an example, for monitoring a business process that follows a carefully designed, prescriptive process model, it could be desirable to carry out the log replay from a model-based perspective (i.e., following the track of the model instead of inserting tokens where they are needed). In doing so one could punish a sequence of missing activities to a greater extent than a single missing activity (which is not the case for the log replay analysis as presented), but this is expected to be a very complex approach as it results in a far more extensive exploration of the model's state space. Moreover, knowing the logging facilities of a workflow product in detail enables a more in-depth evaluation of low level log events such as those related to the life cycle of a task (i.e., *schedule*, *assign*, *start*, *suspend*, ...), and the availability of time stamps makes the verification of time constraints, such as meeting a deadline, possible.

Finally, the incorporation of other perspectives is expected to enrich the conclusions derived from conformance analysis. For example, the evaluation of the organizational perspective (i.e., groups and roles) might provide insight into diverging processes in different departments of a company.

References

[1] W.M.P. van der Aalst. Business Alignment: Using Process Mining as a Tool for Delta Analysis. In J. Grundspenkis and M. Kirikova, editors, *Proceedings of the 5th Workshop on Business Process Modeling, Development and Support (BPMDS'04)*, volume 2 of *Caise'04 Workshops*, pages 138–145. Riga Technical University, Latvia, 2004.

[2] W.M.P. van der Aalst and K.M. van Hee. *Workflow Management: Models, Methods, and Systems*. MIT press, Cambridge, MA, 2002.

[3] W.M.P. van der Aalst, A.H.M. ter Hofstede, B. Kiepuszewski, and A.P. Barros. Workflow Patterns. *Distributed and Parallel Databases*, 14(1):5–51, 2003.

[4] W.M.P. van der Aalst and A.K.A. de Medeiros. Process Mining and Security: Detecting Anomalous Process Executions and Checking Process Conformance. In N. Busi, R. Gorrieri, and F. Martinelli, editors, *Second International Workshop on Security Issues with Petri Nets and other Computational Models (WISP 2004)*, pages 69–84. STAR, Servizio Tipografico Area della Ricerca, CNR Pisa, Italy, 2004.

[5] W.M.P. van der Aalst and M. Song. Mining Social Networks: Uncovering Interaction Patterns in Business Processes. In J. Desel, B. Pernici, and M. Weske, editors, *International Conference on Business Process Management (BPM 2004)*, volume 3080 of *Lecture Notes in Computer Science*, pages 244–260. Springer-Verlag, Berlin, 2004.

[6] W.M.P. van der Aalst, B.F. van Dongen, J. Herbst, L. Maruster, G. Schimm, and A.J.M.M. Weijters. Workflow Mining: A Survey of Issues and Approaches. *Data and Knowledge Engineering*, 47(2):237–267, 2003.

[7] W.M.P. van der Aalst and A.J.M.M. Weijters, editors. *Process Mining*, Special Issue of Computers in Industry, Volume 53, Number 3. Elsevier Science Publishers, Amsterdam, 2004.

[8] W.M.P. van der Aalst, A.J.M.M. Weijters, and L. Maruster. Workflow Mining: Discovering Process Models from Event Logs. *IEEE Transactions on Knowledge and Data Engineering*, 16(9):1128–1142, 2004.

[9] Pallas Athena. *Flower User Manual*. Pallas Athena BV, Apeldoorn, The Netherlands, 2002.

[10] H. de Beer. *The LTL Checker Plugins: A Reference Manual*. Eindhoven University of Technology, Eindhoven, 2004.

[11] J.E. Cook, C. He, and C. Ma. Measuring Behavioral Correspondence to a Timed Concurrent Model. In *Proceedings of the 2001 International Conference on Software Mainenance*, pages 332–341, 2001.

[12] J.E. Cook and A.L. Wolf. Software Process Validation: Quantitatively Measuring the Correspondence of a Process to a Model. *ACM Transactions on Software Engineering and Methodology*, 8(2):147–176, 1999.

[13] G. Cugola, E. Di Nitto, A. Fuggetta, and C. Ghezzi. A Framwork for Formalizing Inconsistencies and Deviations in Human-centered Systems. *ACM Transactions on Software Engineering and Methodology*, 5(3):191–230, 1996.

[14] J. Desel and J. Esparza. *Free Choice Petri Nets*, volume 40 of *Cambridge Tracts in Theoretical Computer Science*. Cambridge University Press, Cambridge, UK, 1995.

[15] J. Desel, W. Reisig, and G. Rozenberg, editors. *Lectures on Concurrency and Petri Nets*, volume 3098 of *Lecture Notes in Computer Science*. Springer-Verlag, Berlin, 2004.

[16] B.F. van Dongen and W.M.P. van der Aalst. Multi-Phase Process Mining: Building Instance Graphs. In P. Atzeni, W. Chu, H. Lu, S. Zhou, and T.W. Ling, editors, *International Conference on Conceptual Modeling (ER 2004)*, volume 3288 of *Lecture Notes in Computer Science*, pages 362–376. Springer-Verlag, Berlin, 2004.

[17] B.F. van Dongen, W.M.P. van der Aalst, and H.M.W. Verbeek. Verification of EPCs: Using Reduction Rules and Petri Nets for Systems Engineering: A Guide to Modeling, Verification, and Applications. In *17th International Conference, CAiSE 2005, Porto*, pages 372–386. Springer-Verlag, Berlin, 2005.

[18] N.E. Fenton and S.L. Pfleeger. *Software Metrics - A Rigorous & Practical Approach (2nd Edition)*. PWS Publishing Company, Boston, 1998.

[19] M. van Giessel. Process Mining in SAP R/3. Master's thesis, Eindhoven University of Technology, Eindhoven, 2004.

[20] G. Greco, A. Guzzo, L. Pontieri, and D. Saccá. Mining Expressive Process Models by Clustering Workflow Traces. *Proc of Advances in Kowledge Discovery and Data Mining, 8th Pacific-Asia Conference (PAKDD 2004)*, pages 52–62, 2004.

[21] D. Grigori, F. Casati, M. Castellanos, U. Dayal, M. Sayal, and M.C. Shan. Business process intelligence. *Computers in Industry*, 53(3):321–343, 2004.

[22] IDS Scheer. ARIS Process Performance Manager (ARIS PPM): Measure, Analyze and Optimize Your Business Process Performance (whitepaper). IDS Scheer, Saarbruecken, Gemany, http://www.ids-scheer.com, 2002.

[23] F. Keller, P. Tabeling, R. Apfelbacher, B. Gröne, A. Knöpfel, R. Kugel, and O. Schmidt. Improving Knowledge Transfer at the Architectural Level: Concepts and Notations. In *Proceedings of The 2002 International Conference on Software Engineering Research and Practice, Las Vegas)*, 2002.

[24] G. Keller and T. Teufel. *SAP R/3 Process Oriented Implementation*. Addison-Wesley, Reading MA, 1998.

[25] L.M. Kristensen, S. Christensen, and K. Jensen. The Practitioner's Guide to Coloured Petri Nets. *International Journal on Software Tools for Technology Transfer*, 2(2):98–132, 1998.

[26] J.B. Kruskal. An Overview of Sequence Comparison. *Time Warps, String Edits, and Macromolecules: The Theory and Practice of Sequence Comparison*, pages 1–44, Addison-Wesley, Reading MA, 1983.

[27] P. Liggesmeyer. *Software-Qualität – Testen, Analysieren und Verifizieren von Software*. Spektrum Akademischer Verlag, Heidelberg, Berlin, 2002.

[28] A.K.A. de Medeiros, A.J.M.M. Weijters, and W.M.P. van der Aalst. Using Genetic Algorithms to Mine Process Models: Representation, Operators and Results. Technical report, BETA Working Paper Series, WP 124, Eindhoven University of Technology, Eindhoven, 2004.

[29] M. zur Mühlen and M. Rosemann. Workflow-based Process Monitoring and Controlling - Technical and Organizational Issues. In R. Sprague, editor, *Proceedings of the 33rd Hawaii International Conference on System Science (HICSS-33)*, pages 1–10. IEEE Computer Society Press, Los Alamitos, California, 2000.

[30] T. Murata. Petri Nets: Properties, Analysis and Applications. *Proceedings of the IEEE*, 77(4):541–580, April 1989.

[31] Mike O'Docherty. *Object-Oriented Analysis and Design: Understanding System Development with UML 2.0*. John Wiley and Sons, 2005.

[32] A.W. Scheer. *ARIS: Business Process Modelling*. Springer-Verlag, Berlin, 2000.

[33] H.M.W. Verbeek. *Verification of WF-nets*. PhD thesis, Eindhoven University of Technology, Eindhoven, The Netherlands, 2004.

[34] A.J.M.M. Weijters and W.M.P. van der Aalst. Rediscovering Workflow Models from Event-Based Data. In *Proceedings of the Third International NAISO Symposium on Engineering of Intelligent Systems (EIS 2002)*, pages 65–65. NAISO Academic Press, Sliedrecht, The Netherlands, 2002. Full paper on CD-rom proceedings.

[35] H. Zuse. *Software Complexity – Measures and Methods*, volume 44 of *Programming Complex Systems*. Walter de Gruyter & Co., Berlin, New York, 1991.