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RESEARCH ARTICLE

Business Process Models in the Context of Predictive Process Monitoring

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Abstract: Predictive process monitoring is a subject of growing interest in academic research. As a result, an increased number of papers on this topic have been published. Due to the high complexity in this research area a wide range of different experimental setups and methods have been applied which makes it very difficult to reliably compare research results. This paper's objective is to investigate how business process models and their characteristics are used during experimental setups and how they can contribute to academic research. First, a literature review is conducted to analyze and discuss the awareness of business process models in experimental setups. Secondly, the paper discusses identified research problems and proposes the concept of a web-based business process model metric suite and the idea of ranked metrics. Through a metric suite researchers and practitioners can automatically evaluate business process model characteristics in their future work. Further, a contextualization of metrics by introducing a ranking of characteristics can potentially indicate how the outcome of experimental setups will be. Hence, the paper's work demonstrates the importance of business process models and their characteristics in the context of predictive process monitoring and proposes the concept of a tool approach and ranking to reliably evaluate business process models characteristics.

Keywords: Business Process Management — Predictive Process Monitoring — Business Process Model Metrics

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1. Introduction

In recent years, organizations keep on having a high interest to get data-driven insights from day-to-day business operations. One emerging opportunity to improve process performance is to train prediction models. Predictive process monitoring (PPM) exploits process data and aims to predict a user-specified need during runtime. Due to the high complexity of the PPM methodology, empirical evaluation so far has used different setups and benchmarks. In detail, different input data, prediction techniques, domains and prediction goals hinder the comparison. This circumstance makes it difficult to reliably compare the applicability and accuracy of research results. A lack of an exhaustive comparison in the presentation of results is given.

To address the aforementioned gap, this paper focuses on the relevance of business process models. Business process models and their characteristics as one part of the PPM methodology can be assigned to input data. The motivation is to identify if business process models are considered as crucial during academic research and further how business process model characteristics can contribute to academic research. From the authors point of view business process models are vital when documenting, improving, automating, comparing, and predicting existing business processes. As a result, it is necessary to evaluate the business process model characteristics and contextualize it. However, the goal of the work is limited to identify a need of transparency and comparability in the area of PPM rather than identifying influential characteristics. Further, a web-based tool approach gets proposed that can fill the identified gap.

The paper is structured as follows: the second chapter summarizes the main terms related to this work: Business Process Management (BPM), PPM and Business Process Model Metrics. In chapter three, relevant experimental approaches in the area of PPM are described. Chapter four analyses the results based on the research questions derived in chapter three. Chapter five discusses the identified research problem and proposes two approaches to solve the problem: the concept of a web-based business process model metric suite, and to promote a ranking of metrics in the area of PPM. Finally, the paper concludes by summarizing the academic contribution and identifying topics for future work.

2. Background

2.1 Business Process Management

BPM is a set of methods, tools and techniques to see how work is performed in an organization [1]. As a central element of contemporary organizations, BPM can support and monitor processes that are for example subject to policies, regulations, and laws. The capability to optimize or support business decisions while running on an enterprise resource planning or workflow system is known as business activity monitoring (BAM) [2]. However, BAM does not provide predictive solutions for an individual running process instance. That is where PPM comes into play. PPM focuses on exploiting generated process data to provide business insights that allow business users to proactively take countermeasures during runtime before they occur.

2.2 Predictive Process Monitoring

The PPM methodology aims to predict the future of quantifiable values during a running process execution [3, 4]. The core of every experimental PPM setup is to build an accurate prediction technique. In the research field of PPM the frameworks proposed by [5, 6] are commonly used when performing experiments. In general, the methodology can be divided on a very high level of abstraction into a training and a runtime phase as visualized in figure 1.

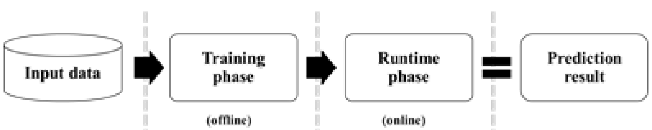

Figure 1. Experimental setup of a predictive process monitoring method

In the first phase, the prediction model is built from finished (offline) input data. Even though the main input data for predictive monitoring methods are finished traces, it further can be classified according to [7] in four different perspectives: the control-flow perspective (concerns the order and relation of activities), the data-flow perspective (concerns the data attributes attached to events), the time perspective (concerns various types of duration such as service times, flow times, waiting times) and the resource/organization perspective (concerns the resource executing the event or corresponding activity). Depending on the type of predictive model it is not necessary to provide all perspectives for training. For example, [5] differentiates between process-aware and non-process aware predictive models. Approaches that are process-aware consider the control-flow perspective as input data explicitly whereas methods that are non-process aware consider the control-flow perspective implicitly. Consequently, after identifying the input data it is necessary to describe an encoding to prepare the relevant information of the process data and finally use the manipulated data to train the predictive model. In general, several predictive models can be considered for training. A common typification is to divide models between classification and regression approaches. The selection of predictive models depends primarily on the type of prediction value (categorical or numeric). Further, the type of predictive model is important for the accuracy assessment: in case of classification methods classification measures such as precision are used. In case of regression methods regression measures such as root-mean squared error are used.

In the second phase, the trained predictive model exploits data corresponding to running (online) traces to predict the outcome during runtime [3]. Based on the prediction result of these traces, the idea is to enable the business to proactively improve process performance and mitigate risks [8]. There are many scenarios where it is useful to have reliable process prediction results, such as predicting compliance violations [9], the remaining sequence of activities [10], or the remaining execution time of a case [11, 12]. For a better understanding concerning the type of prediction outcome, [13] has identified three main macro-categories: numeric (concerns e.g. the remaining time of an ongoing execution or the costs), categorical (concerns e.g. the class of risk) and the sequence of activities (concerns the prediction of the sequence of future activities).

2.3 Business Process Model Metrics

Business process models, regardless whether it is modelled in BPEL [14], EPC [15], BPMN [16] or Petri Nets [12] tend to grow lager and become more complex whenever new business process model characteristics are introduced into an existing process model [17]. In the following, business process model characteristics imply flow objects (events, activities, and gateways) and connecting objects (sequence flow). However, the notation does not indicate if the business process model is provided manually or automatically. Building them manually by users can be very difficult depending on the complexity of the model. Therefore, [18] suggests that if no documented process model exists, or if the process extends across multiple systems, it may be generated automatically through process mining approaches [19, 20] as executed in [21, 22, 23]. Highly complex business process models are error-prone, difficult to understand, to maintain and to manage. Consequently, [24] proposes two approaches to handle complexity and thus keep the highest utility for all stakeholders: First, try to avoid complexity by reducing it. Secondly, control the complexity by metrics.

The paper follows the idea to control the complexity by metrics, meaning measuring business process model characteristics using metrics. Due to the high number of characteristics that contribute to the complexity of a business process model, a variety of valuable metrics have been proposed in the last few decades. This situation is well-known from measuring software complexity. A summary of business process model metrics is provided in table 1. Table 1 is sorted by year of proposal and provides the following information: The first column references the academic paper for easy access, the second column shows the year of proposal and the last column the field of metric. The table structure is also followed in the rest of this subsection.

Table 1. Summary of business process model metrics

Author	Year of Proposal	Business Process Model Metric(s)
[25]	2010	Structural Metrics
[26]	2010	Coupling Metrics
[27]	2009	Complexity Metrics
[28]	2007	Error Metrics
[29]	2006	Conceptual Modeling Metrics
[30]	2006	Complexity Metrics
[31]	2006	Cognitive Complexity Metrics
[32]	2005	Complexity Metrics
[33]	2001	Complexity Metrics

[25] proposed a variety of structural metrics to identify significant predictors for business process model quality. [26] proposes coupling metrics which measure the functional and informational dependencies between the tasks/processes in a business process model. [27] present three complexity metrics that have been implemented in the process analysis tool ProM. [28] provides a set of six metrics to predict errors in business process models. [29] present a suite of metrics for the evaluation of business process models based on the FMESP framework which was developed in order to integrate the modeling and measurement of software processes. [30] defined business process model metrics by gathering insights from software engineering, cognitive science, and graph theory. [31] developed metrics to support the communication between stakeholders by measuring the cognitive complexity of business process models. [32] proposes the metric control-flow complexity (CFC) and discuses to what extent a process is difficult to analyze, understand and explain. [33] summarizes alternative complexity measures discovered in literature.

The result shown in table 1 is similar to research conducted in [34, 35]. Additional, the paper published by [24] presents a classification and an overview of business process metrics and gives an example of implementing these metrics using the ProM tool.

3. Literature review

In order to retrieve and select relevant experimental papers in the area of PPM, a literature review was conducted. The purpose is to analyse the PPM research area in a thorough and unbiased manner. The methodology is adapted to a systematic literature review (SLR) as proposed by [36]. The review differs therein that the literature background gets merged from already conducted literature reviews instead of conducting one from the scratch. Thus, the following procedure ensures a rigorous and complete documentation by specifying the research questions, the search protocol and the selection criteria. Below, the research questions (RQ) are formulated, literature background is identified and selection criteria are defined. In line with the selected scope, the paper aims to answer the following research question:

RQ (Methodology): “How do business process models contribute to the research field of predictive process monitoring?”

In line with the main RQ, the paper also answers the following sub-research questions:

Sub-RQ1 (Techniques): “Do predictive techniques affect the relevance of business process models?”

Sub-RQ2 (Metrics): “What business process model characteristics are currently used as a benchmark?”

Next, the review focuses on a broad literature background which should include substantial contributions and the underlying fact that PPM can rely on different setups. In the first step, already conducted literature reviews by researchers in the area of PPM got identified. This approach carries the following benefits: The identified reviews offer different objectives which indicate a broad literature background in the research field and the retrieved studies are already matched against several selection criteria by their authors to confirm their relevance and quality. In addition, the literature reviews were generally applied to well-known electronic literature databases in the field of computer science such as ResearchGate, arXiv, Elsevier, IEEE Xplore and Springer. The result of identified literature reviews is shown in table 2 which is sorted by publication date and provides the following information: The first column references the academic paper for easy access, the second column shows the year of publication, the third column the period of time the SLR has covered and the last column the number of papers identified for each SLR.

Table 2. Conducted SLRs in the area of PPM sorted by publication date

Author	Publication date	Years covered	Number of Papers
[37]	2020	2011-2019	39
[23]	2019	2005-2017	14
[38]	2019	2005-2017	53
[5]	2018	2010-2016	41
[13]	2018	2005-2018	51

In [5] and [38], the most representative time prediction setups of business processes were summarized. Even though both papers had the same intention, the methodology differs. The review by [13] tackles the issue of the high variety of techniques and developed a value-driven framework based on prediction types. [23] presented a categorized collection of outcome-oriented PPM methods to enable researchers to compare methods in a unified setting. Finally, [37] contributed to the knowledge domain by developing a taxonomy of three business use cases to identify relevant papers and thus possibilities for collaboration between academia and industry. In conclusion, the identified literature background includes in total 198 papers, 108 excluding duplicates. Duplicates are defined as papers that appear in more than one review result that have the identical title and author(s) [39].

After preparing the literature background, the second step is to select search strings that are relevant to the scope of the paper. These search strings then are applied to the identified literature background to retrieve findings that contain at least one of the strings in the abstract or full text of the paper. The following six search strings are used as keywords. They were derived on the one hand, from the terms introduced in chapter 2 and on the other hand, from terms that can indicate an impact on the research area. Presuming that different authors might use a variety of wordings, several search strings were used to obtain a more exhaustive set of relevant phrases:

"limitation" – a paper that has mentioned limitations

"influence" – a paper that has mentioned influencing factors

"affect" – a paper that has mentioned factors that affect the result

"complexity" – a paper that has mentioned complexity

"characteristics" – a paper that has mentioned characteristics

"process model" – a paper that has considered the process model

Because the literature background does not encompass areas outside of PPM, the search strings were not combined in a more specific way and applied to all 108 unique papers. One of the threats to validity of the literature review relates to the potential selection bias in the literature background. To minimize it, the result after filtering by search strings is documented on a sufficient level of detail in table 3. To replicate the search, the column "unverified findings" includes all initial findings by search string.

Table 3. Applied search strings to the 108 unique papers

Search String	Date of Search	Unverified findings	Verified findings
limitation	07.07.2020	30	8
influence	07.07.2020	47	15
affect	07.07.2020	33	5
complexity	07.07.2020	47	16
characteristics	07.07.2020	63	28
process model	07.07.2020	67	45

The search was conducted in July 2020 and resulted in 287 unverified findings. An unverified finding stands for one match after conducting the search by search string. Consequently, each search string can occur more than once in a paper. This situation may lead to an increased number of unverified findings with regard to the total amount of papers shown in table 2. However, to determine if a finding can be considered as valuable, the unverified findings and their context need to be examined. This was accomplished by reading each paragraph containing the search string. To be considered as a verified finding, the content must have a clear link to the business process model and/or its characteristics. The application of the examination resulted in 70 relevant studies and 109 verified results out of 108 unique papers and 287 unverified results.

4. Assessment of business process models in the context of PPM

In this section the 109 verified findings that contribute to the formulated RQ get presented. Specifically, the aim is to answer the main RQ (How do business process models contribute to the research field of predictive process monitoring?), Sub-RQ1 (Do predictive techniques affect the relevance of business process models?) and Sub-RQ2 (What business process model characteristics are currently used as a benchmark?). The analysis of the verified findings in the context of the RQ reveals that business process models can be considered in academic research from three different perspectives: First, as input data, secondly as a benchmark and lastly as influencing factor for the prediction outcome.

4.1 Business process models as input data

As introduced in section 2.2, input data can be categorized in four different perspectives. One of them is the control-flow perspective which relates to the order of activities and the causal relations between them. Thus, the control-flow perspective is logically linked to business process models. Further, [5] uses the knowledge of business process models in experimental setups to differentiate between prediction models, namely process-aware and non-process aware approaches. Consequently, business process models as input data can affect the selection of prediction models and therefore change the experimental setup assuming that the business process model is the starting point. Pretending the question gets asked the other way around, namely if predictive techniques affect the relevance of business process models Sub-RQ1 can be answered. Considering the categorization by [5] the selection of predictive methods can depend on the availability of business process models as input data in combination with the type of predicted value (categorical or numeric). If the input data is not providing the process model and it can not be generated manually or automatically (for example by using the technique process mining) the experimental setup in terms of prediction models is limited. Whereas as long as the business process model is provided, the experimental setup seems not to be limited at all. A detailed description of process-aware and none process-aware methods and further information are summarized in [5] in table 2 and 3.

4.2 Business process models as benchmark

Furthermore, the analysis addresses Sub-RQ2 by answering the question how business models and their characteristics are documented and how researcher use the data. The analysis shows that researchers have used business process model data in two ways: First, in a data driven way and secondly in a functional way. The term data driven refers to properties such as available cases and number of executed activities [22, 23]. This means the metrics are business process model related but do not apply to their characteristics. However, researchers have also focused on the functional part of business process models by providing information about the model's characteristics. Characteristics can be on the one hand a simple list of unique objects as documented by [10, 40]. On the other hand, metrics can be more complex such as the number of sub paths and the largest path length [41].

Although the documentation of business process models and their characteristics in recent research work can be observed, it seems that no standardization for comparability is established. Moreover, even some authors document metrics where it is not clear how to interpret them. In conclusion Sub-RQ2 can get answered: The general lack of documentation of business process model characteristics and the missing standardization and interpretation lead to the lack of comparison of research results based on business process models. Consequently, no metrics are consciously used as a benchmark yet.

4.3 Business process models as influencing factor for prediction accuracy

The most important information of business process models is to specify causal relations between different objects (see section 2.3). For example, the simplest business process models are where activities must be processed in a sequence. Models that contain multiple process variants besides exclusive gateways such as loops, overlapping loops and parallelism increase the number of potentially outcomes of a process and therefore can have a greater impact on the accuracy of prediction. The following observations strengthen the assumption that business process models can influence the prediction accuracy. [41] mentions in his work, when dealing with more complex business process models for example including overlapping loops he has to extend his work. The comment indicates that the complexity of business process models can affect the prediction accuracy. Further, [42] claims that selecting the appropriate path to train a prediction model has an important impact on the model's prediction accuracy. From this assumption can be derived, that the business process model characteristics can have an impact on prediction performance. [43] mention briefly that a high process variability may decrease the precision of predictions. Lastly, [21] describes that loops and parallelism can influence the number of potential future outcomes and therefore need to be considered by the prediction model to reliable predict the likelihood to which each of the future outcome will occur. In summary, it can be observed that researchers are aware of business process model characteristics and their impact on the prediction outcome. However, only general assumptions are mentioned which indicates that there is no clear understanding what metric to what extent can influence the prediction accuracy.

In conclusion, the main RQ has been tackled in the context of this work. The result of the analysis according to the number of identified papers strengthens the assumption by a success rate of 76% (70 relevant papers out 108 papers) that business process models are recognized in the research area of PPM. Further, the analysis reveals that the awareness and potential influence of business process models can be divided in three perspectives: input data, benchmark, and as influencing factor for the prediction outcome. However, the observation further shows that business process models do not contribute to the research field in a reliable and sufficient manner, even they are a firm part of experimental setups. To address this very specific gap, the following chapter describes the area of concern and how it can be improved.

5. Research problem

The analysis reveals that the documentation of business process model characteristics differs in the type of applied metrics and is missing a generic nature. This trend is worrying, because metrics can on the one hand provide transparency to compare research results and on the other hand be an indicator for the outcome of research results. For example, business process models that are used as input data for prediction models can further be evaluated in regards of their characteristics. The metrics then can be used as a benchmark for experimental setups and additionally may indicate the accuracy of prediction results.

In order to address the identified research problems, the paper proposes two approaches to solve the problems: First, proposing the concept of a web-based tool to provide a generic view of business process models characteristics and secondly to promote a ranking of metrics to indicate the outcome of prediction accuracy.

5.1 Business process model metric suite

Due to the high number of factors that contribute to a business process model's complexity, a single metric cannot consider all needed aspects. Therefore, a common solution is to associate different metrics within a so-called metric suite. A metric suite provides single metrics, which again measure specific aspects of the complexity of a business process model. Providing a tool to support the evaluation of business process models in an easy and complete way should increase the transparency. A very abstract concept of Preva (an acronym for Process evaluation) is shown in figure 2. The idea is to move the state of the art to evaluate business process models characteristics from ad-hoc solutions to a more general metric-suite-based solution approach. The concept supports the evaluation of business process models with various characteristics from different domains such as financial, healthcare, public administration, or insurance.

From an architecture point of view, Preva consists out of four core components that are executed in the following

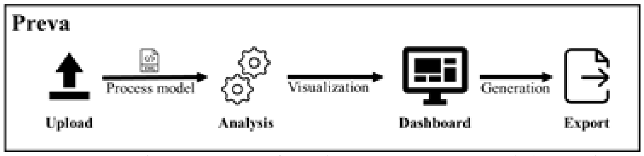

Figure 2. Basic concept of business process model metric suite "Preva"

chronological order: Upload, Analysis, Visualization and Export. The upload component takes the process model as input. Once the business process model is uploaded, the analysis can be triggered and starts to evaluate the uploaded process model. Different metrics shall serve as the basis for analysis. After finishing the analysis, the result is visualized in a dashboard and can be exported as a report.

5.2 Ranking of metrics

Business process model metrics can be ranked according to their impact in the context of PPM. The approach enables researchers and practitioners to contextualize metrics and therefore have a indication what the outcome of the prediction models may be. For example, if an experimental setup includes a very complex business process model that includes various overlapping loops and parallelism, chances are high that the prediction accuracy differs from those that only include one exclusive gateway. Providing a ranking of different metrics based on their impact on research results, allows researcher to have an indication how the business process model may influence the prediction accuracy in a positive or negative manner.

6. Conclusion and future work

This paper contributes to the knowledge domain by providing a novel and profound analysis to better understand how business process models are currently taken into account in the research area of PPM. As a result, three perspectives were identified. Business process models can be used as input data, as a benchmark and as an influencing factor for the prediction outcome. The analysis further observed that the documentation of business process model characteristics differs in the type of applied metrics and is missing a generic nature. In order to solve the gap, the paper has proposed two approaches: First the concept of a web-based metric suite called preva and secondly to rank metrics based on their context. Though, current research has not yet identified which characteristics of business process models can potentially influence the outcome of experimental results in the area of PPM.

In future work, business process model metrics can be made available in a more sophisticated way by providing a web-based metric suite. It allows the user to access the tool through a web browser and makes metrics available. Consequently, the tool then can be applied automatically in future research activities to provide a benchmark for research results. The tool ensures to evaluate a large amount of business process models in a standardized form with less effort and in a short period of time. This approach is also favoured because of its generic nature which allows it to be used in a high variety of research setups and different contexts. Different context may demand different rankings of metrics. Therefore, ranked metrics can help to gain better insights in the area of PPM. In future work the a prototype of the proposed concept will be developed and influential business process model's characteristics are identified.

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