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Towards the Implementation of Process Mining Techniques for Mining Poorly Structured Business Processes

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Abstract.

The accomplishment of poorly organized tasks results in unstructured behaviors. A Poorly Structured Business Process (PSBP) still has extra problems that are tough to measure and comprehend because of its variety and unpredictability. Furthermore, the need for quick response is evident in operating systems. Indeed, it is vital to investigate potential problems that may develop during the execution of a PSBP. Process mining is significant in this context for understanding business process complexity by studying associated event data for each business process. Therefore, this paper focuses on specific issues related to PSBPs. The first problem is determining PSBPs simplification at runtime based on process mining algorithms. The second problem is controlling PSBP unpredictability while accounting for variable circumstances. The third problem is recognizing the optimal process based on the company's business regulations and conditions.

1. Introduction

Process Mining (PMg) is a unique business intelligence field that incorporates strategies for discovering, monitoring, and improving real processes by gathering knowledge from event logs in information systems. PMg, in fact, connects process and data science (see Van der Aalst [47]).

The modeling, analysis, and optimization of processes is referred to as process science. Optimization (identifying the best potential process implementation using mathematical optimization approaches), BP Improvement (for example, BP Re-engineering), Formal Methods & Concurrency Theory (for example, Six Sigma techniques), Formal Methods & Con (analysis of process behaviors, using, for instance, graphical representation).

Process discovery, conformance checking, and enhancement are the three areas that Van der Aalst et al. [48] identify as part of PMg. The process It automates the business process modeling based on saved event logs. Conformance tests the recent discovered process model against the historical one. The technique purpose is to find bottlenecks and notice discrepancies. Improvement focuses on utilizing the information recorded in event logs to improve or extend the current process model.

To represent process models, PMg focuses on event logs. Thus, PMg can examine BP structures. Complex-structured BPs are unintelligible, unreadable, and susceptible to resources modifications during BPs execution. Poorly organized BPs are, in fact, ill-defined and reliant on easily accessible information. The issue is how to use PMg techniques to generate a simplified and enhanced representation of a PSBP. In this context, PMg can be used for both data-intensive and knowledge-intensive systems since structured processes exist within poorly structured ones. This indicates that the process is primary and, in most cases, static. Knowledge-intensive, on the other hand, places data at the centre, allowing the adjacent processes to make judgments as needed. The information is regarded as crucial. Beyond, circumstances, procedures aren't completely predefined, thus knowledge workers must define them on the fly as needed. Overall, structured BP has predetermined process pathways; however, with PSBP, the case itself is the primary focus.

As a result of its complexity and variety, PSBP continues to have challenges that are difficult to understand and comprehend. Furthermore, it is necessary to give dynamic and instantiate responses to these PSBPs. We provide existing work in section 2 that is connected to those three challenges in the context of PMg: complexity, unpredictability, and dynamicity. Section 3 addresses three difficulties of PSBPs. Indeed, we propose three techniques for dealing with the complexity, variability, and dynamicity issues that PSBPs can provide. PMg techniques are used in the proposed methods. The following is a list of the difficulties that were addressed: The first aspect of complexity is the ability to support complex BPs at runtime by predicting and advising actions. The second source of variability is the management of BPs in accordance with the goals of the users. Finally, throughout the BP implementation, dynamicity brings the concept of adaptation. Finally, we summarize our contributions and wrap up the section. The fourth section concludes the work and discusses future research.

2. State of the Art

Due to their complexity and variety, PSBPs still have more challenges that are difficult to study and comprehend. Furthermore, it is necessary to give dynamic instantiate responses to these PSBPs. In the following paragraphs, we will discuss existing work on those three challenges in the context of PMg: complexity, unpredictability, and dynamicity.

We used three platforms to find publications that addressed these issues: the PMg Wiki, SCOPUS database, and Google Scholar. PMg Wiki is a publication platform that encompasses process mining scientific articles and solely features PMg publications. SCOPUS is the world's largest peer-reviewed literature database. We also looked at

Google Scholar, which provides access to a wide range of academic literature, to avoid skipping some studies.

2.1. Complexity

Many scientific studies have been conducted in the recent decade to address PMg issues. More particularly, methods and techniques for simplifying the representation of PSBPs. We demonstrate the still-present issues PMg applied to PSBPs in this subsection. The key problem is the complexity observed in event logs (Lamghari et al. [28]).

Complex event logs are challenging to handle appropriately in PMG. Fortunately, it is widely accepted that deconstructing processes is the most effective method for dealing with complexity. PMg problems are decomposed into several smaller semi-problems that can be solved quickly using this technique (Kalenkova et al. [33]). There are numerous techniques to segment PMg problems in the literature. However, different authors used diverse approaches for BP decomposition: Authors like (Van der Aalst et al. [45]) develop the split concept. Then, (Munoz-Gama et al. [35]) suggest the use of the Single Current mechanism. Next, the concept of process containers (Van der Aalst [46]) is appeared. Last, (Irshad et al. [22]) and (Munoz-Gama et al. [36]) favorize the four contradictory aspects of quality, particularly in conformance checking decomposition.

Furthermore, each PMg decomposition study has significant limitations that must be addressed in future research. The most pressing issue is determining the best method for mining constructed event logs generated from a complex event log. The structural methods use concepts of the following approaches (Artem et al. [2]; Polato et al. [39]; Polyvyanyy et al. [40]; Oulsnam [38]). Only poorly structured acyclic stiff parts are treated with parallelism in the first two approaches. The second and third techniques are restricted to stiff parts with no concurrency (restricted decision points). This is necessitated the combination hybrid between the above techniques. To do so, to accomplish so, (Augusto et al. [4]) have used a modern technique. This is a way for producing a structured BP from event logs that uses a discover-and-structure approach. This method is based on the concept that rather than trying to directly find structured blocks of the process model, the process model quality can be found by determining a reduced representation of a PSBP and converting it to a simplified process model. The proposed method employs the following structure strategies to discover the structured BP:

(1) Gateway structuring (repair the poorly structured gate depiction).
(2) Removal of clones (removal of repeated activities and, by necessity, actions from the process model).
(3) Restoring structural integrity (validating the accuracy of the obtained process model). BPMN is used as a process model representation language in this method.
(4) Repairing structural integrity (verify Strengthening of the obtained process model). BPMN is used as a process model representation language in this method.

Running poorly organized systems results in unstructured behavior. Due to their complicated structure, they are difficult to analyze and comprehend. Furthermore, this complexity issue must be addressed throughout the implementation of operational support measures. Several techniques have been developed in this context. Since the release of the PMg Manifesto (Van der Aalst et al. [43]), we have been focusing on scientific articles released from 2011 to the first half of 2022 and matched exactly with our issues:

First, (Nakatumba et al. [37]) develop an operational backup, which defines concepts, their properties and the existing relationships between these concepts using the academic PMg framework (ProM). This meta-model covers simple, evaluate, forecast, and propose queries. Second, (Folino et al. [18]) present a holistic strategy that uses learned behaviors to estimate visible and invisible traces of different classes. The signature patterns revealed allow for the differentiation of various types of behavior. Third, (Conforti et al. [9]) provide a method for predicting process vulnerabilities by employing regression trees to prior process execution logs while accounting for a range of PMg elements. The suggested technique accomplishes this by assisting process participants in making decisions: activities, data representatig process model. Similarly, (De Leoni and Van der Aalst et al. [10]) investigate a technique that anticipates remaining processing time and suggests risk-reducing measures. Fourth, (Hompes et al. [21]) present a solution for preventing the unwanted behavior in subsequent executions. This is done using the Markov Cluster (MCL) technique, which can detect changes in a process based on the perspectives chosen. The paradigm purpose (Van der Aalst and Dees [11]) is for estimating the percentage of nonlinear behavior from event logs. It could correlate and cluster dynamic behavior. The framework can anticipate the operator of activities, the time till the process instance ends, the following activities to be completed, and the output of each process instance. Fifth, (Mehdiyev et al. [34]) show a new deep learning strategy that encompasses different levels of BP knowledge to recognize suitable future activities that must be executed. This is based on finished process instances. This is done to anticipate BP occurrences and initiate timely interventions in the event of undesirable drawbacks from the expected process. Sixth, (Folino et al. [18]) develop a spectrum for identifying and analyzing BP sub-processes in real time, based on both a novel incremental approach to the discovery of an ensemble-based deviance detection model and an innovative incremental method for developing an ensemble-based deviation detection model. Furthermore, (Lin et al. [33]) provide a strategy for addressing the problem by employing deep learning methods to learn the impact of past events on future events. It is an Event Sequence predictive model with multiple attributes. Indeed, none of the mentioned studies that discuss the use of PMg for operational assistance use orchestration of all existing PMg operations. Some, solely provide operational assistance to organized BPs.

The capacity to predict the trend of running process instances in terms of many characteristics, such as estimated completion time, would help company managers to respond quickly to unfavorable events and save losses. As a result, an operational strategy is required to resolve the complexity problem in operational assistance operations (detection of infractions, prediction of events, and action recommendations).

2.2. Personalized BP and variability

BP variability can be defined as a system that allows users to investigate using a variety of methods, depending on their goals. Different behaviors can indeed be developed. Indeed, users with similar goals may take distinct sub-processes, then encounter distinct paths known as personalized / configurable business processes, which differ in terms of structure, goal, and outcome. Thus, the main problem is how to emphasize the challenge of acquiring and analyzing the user activity (El faquih et al. [16]; Van der Aalst et al. [48]). The variant idea is used here to recognize either the activity variant or the process model variant. Furthermore, the variation point identifies a key component of the customizable process model. It can be altered with model transformations. As a result, the customizable process model may encompass new decisions made in process variations at either design or runtime. Individual variants of customizable process models can be produced through transformations, such as adding or deleting specific undergoing parts.

As a result, the difficulty in describing BP types stems from the concept of variability (Athukorala et al. [3]). This will vary depending on the situation and need. Even while managing process variability is a difficult undertaking that necessitates the application of specialized standards, methodologies, and technology, it nevertheless involves many characteristics that are not usually defined. In this context, designing the original process model, which represents the process family's commonalities, as well as any required modifications to construct a given process variant, are examples of challenges. Thus, each BP variant is relevant to a distinct context and has a distinct impact on the specified customization criteria. Strong features or unrelated goals, like performance measures or operational restrictions, which dictated patterns to determine the suitable BP, are examples of such criteria. Two primary definitions can be obtained in this context (Van der Aalst et al. [25], Detro et al. [12], La rose et al. [27]):

(1) Restriction-based variation usually commences with a specific process model that includes all process variation behavior. Customization can be accomplished by limiting the configurable process model's behavior. During customization, for example, actions may be skipped or prohibited. In this case, the configurable process model can be thought of all process variants. This form of adjustable process model is also known as configurable process models.

(2) Variability through extension begins at the extreme end of the aforementioned spectrum. The configurable process model does not describe all potential behavior; rather, it depicts the most common or shared behavior among most process variants. The model's behavior must be extended during customization to serve a specific context. To establish a dedicated variety, for example, new activities may need to be added. A customizable process model can be thought of in this context as the intersection of all process variants under consideration.

PMg technologies can be employed to explore and treat BP variability. to manage and decide the best process or sub-process to consider taking.

2.3. Dynamicity

The term "dynamicity" refers to a procedure that allows some BP actions to vary during runtime against varied conditions that are determined by real-time factors. It can be modified in response to changes different environments. Also, we will look at asynchronous processes, which are characterized by their lack of set workflows. Indeed, the control-flow between tasks cannot be predicted ahead of time and must instead occur in real time. Users decide what they want to do and when they want to do it. They also assign tasks to others as a sub-process and develop interactions amongst users. This highlights the difficulties of dealing with dynamic asynchronous processes.

In this sub-section, we investigate studies that tackle 1) PMg approaches with asynchronous BP. 2) Asynchronous BP and dynamicity, and 3) Dynamicity with PMg approaches. In this context, we have observed that (Dustdar et al. [15]) suggested and demonstrated a technique for mining asynchronous processes. The uncertainty here is related to sub-processes with various and enrichment requirements. Furthermore, the adaptive process is unaffected by exogenous alterations. Authors describe four case studies in the healthcare area, specifically in the emergency services (Duma et al. [13], Duma et al. [14]). Here, the process discovery technique is used to show what processes a patient in the emergency services might go through. These examples are combined into a holistic strategy. Also, (Kiedrowicz [25]) proposes an approach for asynchronous BP that incorporates dynamicity by employing local and public sections to perform actions depending on a set of process goals. PMg did not match the asynchronous BP criteria in this investigation. In addition, the paper of (Jain et al. [23]) explored public and private environment alterations as well as variables that could influence BP dynamicity. Some publications, such as (Vasilecas et al. [49]), focus solely on the private context, while others do not specify automated BP operations and do not address modifications appeared in the context of different activities (private to public asynchronous process environment). In addition, (Zhu et al. [51]) show just exterior modifications.

According to the aforementioned studies, few scientific papers investigate the combination of dynamicity, asynchronous BP, PMg approaches, public and private changes in the BP environment, or asynchronous BP-related situations. To do this, we must incorporate dynamicity into asynchronous BP, utilizing PMg techniques and accounting for runtime changes.

2.4. Synthesis

In this section, we have talked about how to forecast, structure, and control unpredictability and dynamicity in PSBPs. This is addressed in the context of PMg. First, we showed the treatment of event logs complexity. It's critical at this point to investigate organized and poorly structured sub-processes. Second, we examined the difficulty of obtaining operational support with complex process models. For example, during the BP execution, it is necessary to conduct subsequent operations. Then we developed the variability challenge, which included a list of concerns that needed to be fixed. Third, we examined the dynamicity difficulty and the need to easily define processes in order to choose the appropriate responsive sub-process.

3. Poorly Structured BP Enhancement Approaches

A BP's structure is altered between simplicity and complexity. This shift is triggered daily by human intervention to fix drawbacks that can be appeared in business process and halt its progression. A wide range of stunning possibilities can be handled here, as well as additional challenges pertaining BP improvement and structure.

First, we suggest a method for dealing with PSBP complexity at runtime. Second, we develop a strategy to address the variability challenge to determine which path should be taken during BP execution. Finally, we propose a technique to address the dynamicity challenge in order to execute PSBPs in a dynamically based on the company's business rules and conditions. These methods have been independently assessed in these articles (Lamghari et al. [4], Lamghari et al. [29]; Lamghari et al. [31]).

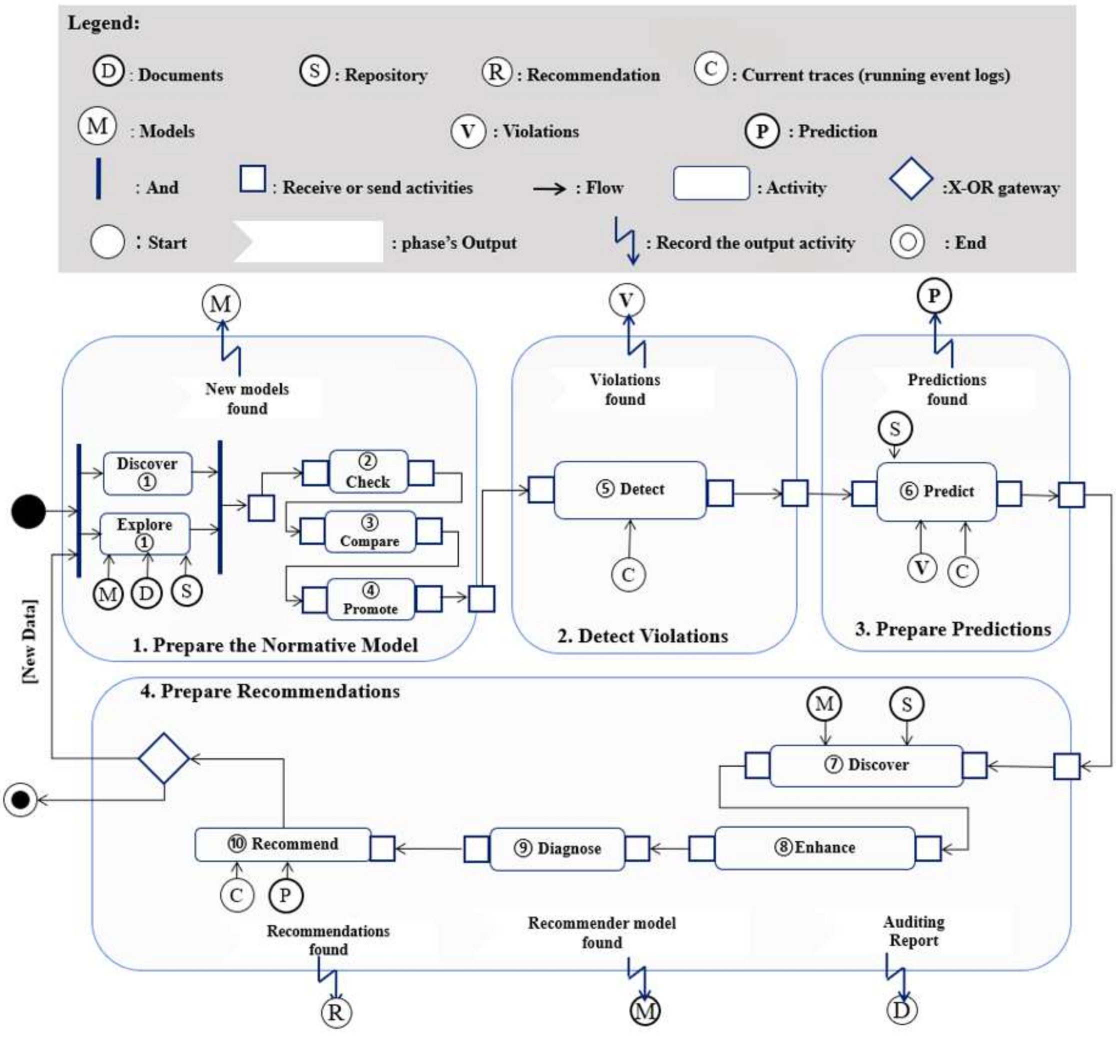

Figure 1: Spectrum for simplifying complex BP.

3.1. Operational support approach

The challenge of forecasting activities during the execution of PSBPs comes from their complex structure. Other PMg techniques are required for this. We use the recently enhanced PMg framework as an example. This paradigm divides PMg types into three groups of ten activities: navigation (discovery, enhancement, and diagnosis), auditing (detect, check, compare, and promote), and cartography (Explore, Predict and Recommend). These ten activities connect current and historical event logs.

The most difficult challenge is determining how historical data can help contemporary conditions. Operational backup systems have been developed for this purpose, with the goal of learning based on pre-existing structured models, normative models, historical data, and current data. As a result, using the actions of Detect, Predict, and Recommend is required. Also important is the emergence of predictive (which seeks to anticipate an outcome that can impact subsequent events) and suitable models in term of the preference of an activity against another activity. The inference models are these two. Operational backup approaches work well with structured BP, but they are still difficult to implement with PSBP. In this regard, there are still concerns with the PSBP operational backup application. (Buijs et al. [8]) can be lowered by reorganising PMg operations to make operational backup for PSBP based on the structured BP version. Other PMg operations such as Diagnosis, Check, Promote, and so on are required for this operation. As a result, determining the order of PMg activities remains a difficult problem.

To that end, the goal of our approach is to create an operational backup strategy for PSBPs that identifies breaches, predicts occurrences, and advises actions in real time. As a result, we recommend integrating the 10 operations of the modified PMg framework in a precise order.

Taking on the topic of PSBP analysis through the orchestration of existing PMg activities in term of developing a comprehensive solution to the complexity problem. Indeed, we go over the steps of our PSBP operational assistance methodology (Cf. Figure 1).

(1) In order to achieve the PSBP operational assistance goal, we need a structured BP, a Standard Initial Normative Model (SINM), and an improved normative model.

(2) In order to obtain the structured BP of a PSBP, we use the simplification algorithm in conjunction with structuring techniques (Augusto et al. [5]). In this case, we choose a heuristics miner algorithm for the discover activity ①. Simultaneously, we investigate ① Recorded information and models to define the initial normative model.

(3) In order to make the improved normative model, an audit approach must be used by performing the following activities (check ②, compare ③ and promote ④).

(4) With the improved normative model and the structured BP in hand, we can detect violations (detect ⑤). This enables the predictive model to predict events (predict ⑥). We can additionnaly recommend ⑩ actions relatively to the resulted diagnosis information (discover ⑦, enhance ⑧ and diagnose ⑨) and the suitable model.

The real process model is denoted as PSBP and as a structured BP. The PSBP used during the structuring techniques employement and the structured BP is mentioned after the structuring techniques employement. A developed normative model is also referred to as a final model. In this sense, our approach is presetend into different phases as shown in Figure 1: We begin by doing five tasks to prepare the normative model: Discover, Explore, Check, Compare, and Promote. The product of this step is an improved normative model. Then, we apply the Detect activity reveal out infractions. We can forecast events in the third phase based on the revealed violation and historical data. Finally, we diagnose data to build a suitable model and obtain appropriate recommendations by combining the Discover, Enhance, Diagnosis, and Recommend activities..

3.2. Self-decided business process

The contribution in this part focuses on mining self-decided BPs (Lamghari et al. [31]). It is true that a proper technique for depicting different behavior is needed. PMg appears to be an intriguing alternative to consider in this regard. Additionally, self-decided BP fluctuation must be managed (Configurable Process Model). Furthermore, in the case of variation points, we need to manage semantic content, in order to advocate one logical approach (see Figure 2).

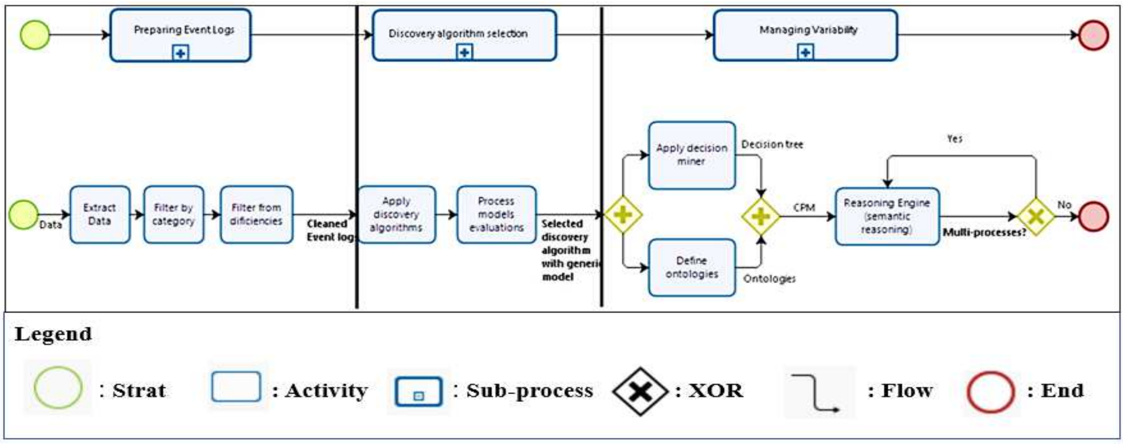

Figure 2: Spectrum for mining self-decided BP.

(1) Configurable Process Model (CfPM): presented with the goal of implementing various process variants into a single model (Gottschalk et al. [19]). As a result, the CfPM allows the extraction of BP variations, which is a process model that differs from the initial. It is more suitable for the application context. This method allows for the representation of the similarities between process variants. This approach encourages model reuse by sharing specifics across multiple variants (Ayora et al. [6]). Management, design, redesign, modelling, and configuration have all been discussed in relation to BP variability. Furthermore, the majority of the suggested methods are manual. Evidently, the construction of the process variant needs the verification of syntactical and semantic levels of resultant models, while existing methodologies

do not distinguish between expected and real process execution, i.e., what arises during process execution may not be expected to happen. As a result, the use of PMg techniques is required because they allow information to be extracted from event logs. Process variants and problems can thus be discovered and corrected by analyzing the generated process model. As a result, a decision miner PMg approach is used to analyze decision points that allow for the description of public factors that influence, choices, and rules. Among the advantages of contextual amplification of the BP are increased in terms of representation and understanding, as well as automation of processes related to the BP's modeling, configuration, evolution, and responsiveness to changing specifications. As a result, the CfPM can be semantically analyzed.

(2) Ontologies and logical or semantic reasoning: The ontology is made up of commonly used terms that describe the domain of interest (Bogarin Vega et al. [7]). The ontology allows for the capture, representation, reuse, sharing, and exchange of knowledge in a specific domain. However, semantic annotation allows knowledge to be shared and reused among applications and agents. Semantic annotation allows for reasoning over the ontology, ensuring its quality by gaining additional information (Liao et al. [32]). To improve the level of BPM lifecycle, semantic enrichment of the BP was proposed with compliance checking technique (Hepp and Roman [26]; Szabo and Verga [42]). Semantic technologies have been used in the CfPM for semantic enrichment (El Faquih et al. [16]) and semantic validation (Fei and N. Meskens [17]).

(3) The variety of self-decided BP makes it challenging to represent (Athukorala et al. [3]). The latter is context and necessity dependent. Managing process variability is a challenging undertaking that needs the use of specialized standards, methodologies, and technologies, yet it still encompasses many undefined components. Indeed, designing the reference process model, which captures the commonalities of the process family, is difficult, as are the alterations required to set a given process variant.

(4) To address these issues, it is beneficial to identify users' behavior (processes of gathering information), i.e., to define the global process model, in order to study the self-decided BP variability and suggest each user's relevant path.

It is also advantageous to manage process variations using ontologies based on semantic reasoning and the CfPM, i.e., selecting the optimal process variant based on a mix of self-decided BP ontologies (Gottschalk et al. [20]). To accomplish these goals, PMg algorithms must be used to mine user-defined BPs. To identify the global process model, the first stage is to choose the most preferred method qualitative requirements based on process model.

The second stage is to manage current process variants in order to suggest the best path based on the user's goal, needs, and engine knowledge. This is accomplished by obtaining the CfPM (process model with variations details) using the decision miner method and applying relevant semantic reasoning of the self-decided BP ontologies. This contribution, in fact, can assess how well PMg algorithms represent self-decided processes, as well as their capability of generating user behavior and find variations, choices, and constraints. Furthermore, it demonstrates the use of semantic reasoning as a decision task that may be paired with PMg.

3.3. Business process dynamicity

The term "dynamicity" refers to a procedure that allows some BP actions to vary during runtime within variable conditions that are determined by real-time factors. It can be modified in response to changes in the private or public environment. In this context, we will look at asynchronous processes, which are characterised by their lack of set workflows. Indeed, the control-flow between tasks cannot be predicted ahead of time and must instead occur in real time. This highlights the difficulties of dealing with dynamic asychronous processes.

In this approach, our contribution (see Figure 3) intends to use PMg techniques to introduce the concept of dynamicity into asychronous BP. We try to show how to use

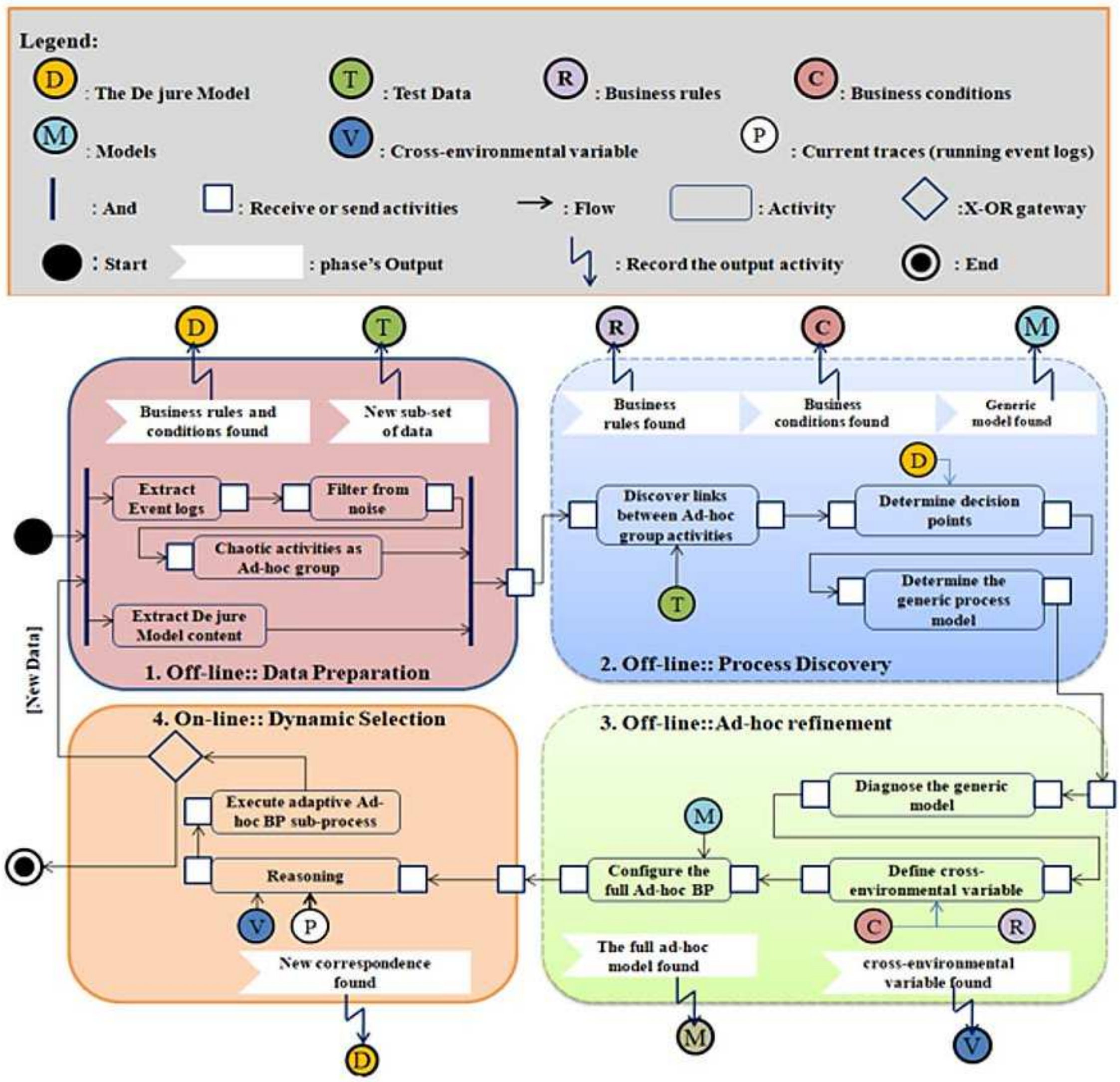

Figure 3: Spectrum for mining self-decided BP.

the process discovery technique to collect information from event logs (offline) in order to model and configure asychronous BP.

The compliance testing technique is then used to show how to pick at runtim acceptable asynchronous BP to specific scenarios (Online). The asychronous BP can be remodeled and reconfigured using the enhancement technique. We present our method for dynamically identifying an adaptable sub-process using PMg techniques for this purpose. This contribution consists of employing PMg techniques to tackle dynamic asynchronous BP.

We are attempting to model asynchronous BP using prior event information and to pick an adaptive sub-process depending on ongoing events. Thus, we broadcast our strategy in these perspectives: offline and online (see Figure 3). We examine event logs in the Offline view to discover the global process. We may also identify the entire asynchronous process model. We strive to adapt our asynchronous BP in the Online perspective, which entails dynamic selection of an adaptive asynchronous sub-process based on specific situations. These circumstances are a type of cross-environmental variable that incorporates business regulations and conditions. Indeed, business conditions are used as a deciding factor for each crossroad. A system of rules developed to serve as a guide for activities or decisions. Public conditions are passed to the private asynchronous BP environment via cross-environmental variables.

4. Conclusion

We provided three approaches employing PMg techniques to cope with PSBP issues in this research. The enhanced PMg framework is considered in the first method. This section offers a set of actions that make use of event log data, found models, and normative models. The Detect, Predict, and Recommend activities are those that deal with running events in the structured BP setting. Because of their complex structure, these three tasks have been designated as an operational assistance system that works effectively on structured BP while remaining a difficult assignment for a PSBP. The use of established PMg tools to study poorly structured processes, from the extraction of a process model based on event data to the recommendation stage, is of particular interest in this respect. For that purpose, we have proposed integrating PMg operations into a PSBP operational assistance approach.

The second approach is created to address relevant issues for self-decided BPs. In fact, we study the use of PMg methodologies to express the global self-decided process model suitable to user behavior. Beyond, users can conduct their research in a variety of methods, depending on their objectives. Users utilize self-decided procedures in this environment, which might differ in terms of importance, structure, and outcomes. Indeed, the decision miner algorithm is necessary to accomplish this step. As a result, you can get a customizable process model. Finally, to regulate self-decided BP variability, a combination of abstracted methods as semantic reasoning by ontologies and the configurable process model can be launched.

The third approach uses PMg techniques to deal dynamically asynchronous BPs. The dynamic selection is not matched, and asynchronous processes are not predefined.

As a result, there is a lack of process adaptation based on real-time inputs. For that purpose, we offer standards that must be followed while defining asynchronous BPs. The asynchronous BP characterized by its globality and dynamicity, i.e., adaptable to changing status in real time (changes). Additionally, we show how PMg techniques are utilized to define asynchronous BP. In this regard, this methodology involves points: The Offline view tries to create a global model by combining the process discovery technique with the frequency idea. The compliance testing technique is used in the Online view to adjust the appropriate asynchronous BP while keeping the flexibility concept in mind. Following the execution, all data will be recorded to improve the asynchronous BP in the future.

As further research, we intend to do additional research to validate the applicability of our approaches using specific case studies: electronic services (e-services), Chaotic activities and IoT event data.

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