SOCIALIZATION OF WORK PRACTICE THROUGH BUSINESS PROCESS ANALYSIS

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Abstract: In today's competitive business era, having the best practice business process is fundamental to the success of an organisation. Best practice reference models are generally created by experts in the domain, but often the best practice can be implicitly derived from the work practices of actual workers within the organization. In this paper, we propose to utilize the experiences and knowledge of previous business process users to inform and improve the current practices, thereby bringing about a socialization of work practice. We have developed a recommendation system to assist users to select the best practices of previous users through an analysis of business process execution logs. Recommendations are generated based on multi criteria analysis applied to the accumulated process data and the proposed approach is capable of extracting meaningful recommendations from large data sets in an efficient way.

1 INTRODUCTION

In a very competitive business era, having the best practice business process is the basis of the success of an organisation. A valuable and often overlooked source of best practice is the experiences and knowledge of individuals who perform various activities within the business process. This knowledge constitutes the corporate skill base and is found in the experiences and practices of individuals, who are domain experts in a particular aspect of the overall operations.

Furthermore, business processes often face a dynamic environment which forces them to have the characteristic of ad-hocism in order to tailor to circumstances of individual process cases or instances. This creates what so called business process variants (Lu et al., 2009). The variants include the creativity and individualism of the knowledge worker, which is generally only tacitly available. Each variant has the same goal but by having different approaches, it may have different time needed, different task set and/or sequence and most likely different cost.

A traditional Business Process Management (BPM) System is not generally capable to select best processes since all instances follow the same process model, and thus there is hardly any variance that can reflect individual/unique approaches. However, some complementary work can be found within the BPM community that long recognized the need to provide flexible business process. Some works show how flexible business process can be achieved by executing variance with certain selection strategies (e.g. lowest cost, cycle time) as mentioned by Vanderfeesten et al. (2008) and Lu & Sadiq (2008). It is expected by having the flexible business process, an organisation can rapidly adjust their business process to suit the environment. But, having a flexible process is not always a solution to achieve the most efficient practice for the organisation. In fact, the more flexible the system, the more a (inexperienced) user may struggle to find the best approach to address a particular case. These users are required to have deep knowledge of the process they are working on (Helen et al., 2008, Schonenberg et al., 2008).

In this paper we will present an approach to providing assistance to users which allows them to select the best process variants been done by previous (arguably experienced) users. Rather than forcing users to make design decisions, we will use the existing knowledge in the BPM system (through execution logs) and select the variants that best meet the required criteria. The approach will guide the future user to get the benefit from user perspective, as well as organisational perspective. The remainder of this paper is organized as follows.

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In Section 2, we specify the problem background and related work. Then, in Section 3 we present the experience driven recommendation service including the details of the analysis. Finally, in the last section, Section 4, we provide a summary evaluation of the proposed approach and conclusions drawn from this work.

2 PROBLEM BACKGROUND AND RELATED WORK

Today, many organisations have implemented BPM system in managing, monitoring, controlling, analysing and optimizing their business process (Aalst et al., 2003). BPM allows organisations to design business process models, execute process instances in accordance with the models, enable users/applications to access task lists and execute task operations (Yujie et al., 2004). The system is meant to implement business strategies phases by modelling, developing, deploying, and managing business process so that organisations can have the benefit of innovation and optimization.

As the phases work in cycle, the overall business process can be improved by revamping various components of the cycle. Business process analysis is the key means to this end. In business process analysis, the business process activities are analysed, mapped, etc (Biazzo, 2000) with the goal of continuously improving the process and related practices to create a better quality of the business process. The efficiency, cost, completeness, and the confidence level of business process are key to quality definition. Business process analysis is an essential prerequisite for organisational change and is needed to create either gradual change or incremental change (Biazzo, 2000).

A number of contributions have been made in the general area of business process analysis. An audit trail of a BPM system is an example on how it can be used to find models which describe the process, organisations, and products. An audit trail contains information about the events i.e. who executes the process, what time was taken, which activity and process instance, etc. All information can then be analysed in many areas as explained by Bozkaya (2009), such as to measure the performance of processes (Hornix, 2007), process discovery (Günther and Aalst, 2007), process conformance (Rozinat and Aalst, 2005), and social networks (Aalst et al., 2005a). Some research also provides the process model as the output of process discovery (Aalst et al., 2004) where from a workflow log, a process model is constructed partially or fully developed, which later can be used for specific purposes, such as discovering patterns of execution (Dubouloz and Toklu, 2005), analyse variance of process model (Tsai and Chen, 2009). Similarly, interaction patterns can also be learnt to cover what social networks exist (Aalst and Song, 2004).

At the same time, business processes are quite often characterized with variance. Variance itself in business process execution is the outcome of many situations, Lu and Sadiq (2008) give examples, such as the disconnection between documented models and business operations, the active change and exception handling, flexible and ad-hoc requirements, and collaborative and/or knowledge intensive work. Various work practices are present in real world, and it incorporates personal approaches and knowledge of workers of benefit to the organisation (Lu and Sadiq, 2006). This especially happens when the organisation have flexible ways to complete tasks.

Figure 1 presents example process models of different process variants. The process models show how same tasks are processed differently in different variants. Tasks here can represent e.g tests to diagnose a reported fault in telecommunication, or investigative activities of an insurance claim etc. The coordinative nodes *Begin*, *End*, *Fork*, *Synchronizer*, *Choice*, and *Merge* shown in the figure are assumed to have typical semantics (WFMC, 1999).

Consider insurance claim process in a health care industry as an example. During insurance claiming process, the same goal could be achieved in multiple ways. As customers vary, e.g regular or VIP customer, with single or family type insurance, and many more criteria, the approaches and steps taken to complete the claim process will be treated differently. In addition, a claims officer will have different approach to handle the claims within the constraints of the insurance policy. Thus leading to the creation of *process variants*.

In the previous work, Lu and Sadiq (2008) present a facility for discovery of preferred variants through effective search and retrieval based on the notion of process similarity, where multiple aspects of the process variants are compared according to specific query requirements.

The useful feature of the approach developed was the ability to provide a quantitative measure for the similarity between process variants. However, the problem is much more complex. The value of a process variant can only be realized if it provides

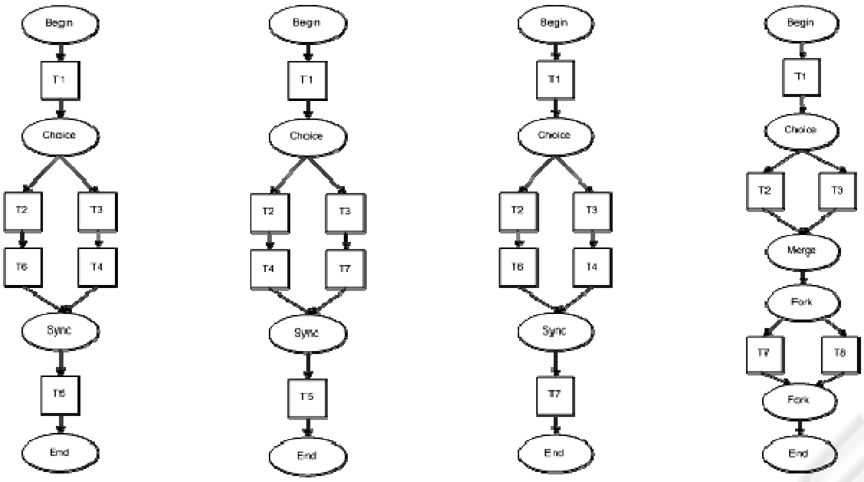

Figure 1: Example process model of process variants.

relevant and meaningful recommendations for others who are working in a similar scenario – so called *socialization of work practice*.

We identify the socialization of work practice as simply providing the best practices which have been done by previous workers to potential future users. In this paper, we will investigate and subsequently define the criteria for identification and ranking of precedents that working communities may utilize.

The proposed *experience driven recommendation service* (see section 3) has the potential to achieve an effective solution for all stakeholders. This is achieved by utilizing the experiences built by expert claim processing officers. We assume that these experiences are manifested in process variants (as proposed by Lu and Sadiq (2008), thus process variants have the capacity to externalize the previously tacit knowledge found in individual experiences.

It is also important to understand the role of experience in organizational learning as experience is a fundamental notion of our work. Experience has a potential value to enrich the knowledge sharing and knowledge transfer between learners, as learning process is the process of knowledge transfer between tacit and explicit knowledge.

In our research, we propose a recommendation service based on the experience of business process users. The recommendation service is initiated by the system by analysing the history of executed activities. The recommendation service then supplies the system with a recommendation result which is the best practice among various practices of different workers.

3 EXPERIENCE DRIVEN RECOMMENDATION SERVICE

In this section, we present our approach to socialization of work practice through a Experience Driven Recommendation Service (EDRS). The EDRS is an add-on to the BPM system that provides the capability to identify and rank previous process variants against a set of criteria, and thereby assist current users to deal with specific process cases in the *best* possible way as demonstrated by the practices of previous users.

3.1 EDRS Architecture

Basically, EDRS is an add-on to the BPM system to provide the information on best past practice. The experience driven recommendation service relies on previously recorded execution logs which contain information on various aspects of the process including execution times, costs and resources used etc.

We assume a typical schema of the execution log (Grigori et al., 2004) typically structured as a set of timed events. Thus, further information such as the tasks and structure of various variants, number of times a variant has been used etc. can also be extracted.

The EDRS consists of three main components: the process mining component, experience driven analysis component, and EDRS recommender component. The process mining component (similar to those proposed in Aalst et al. (2005b) is responsible for analysing the execution logs and producing the process models of various variants.

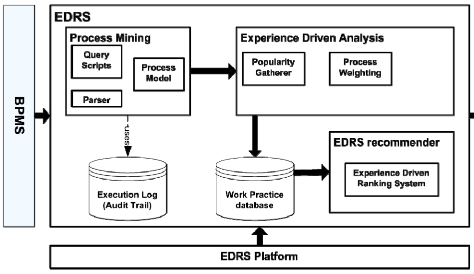

Figure 2: EDRS Architecture.

The experience driven analysis component creates information on process popularity (number of instances against a given variant) and respective weight (where weight is a quantification of time and resources of a particular process instance) and store it in the so-called Work Practice Database. The EDRS recommender will produce a sorted list of selected processes (variants) from the work practice database.

In summary, the recommendation setting used in the EDRS architecture will be based on multi criteria system which will try to calculate based on the process structure (task sequence), the time taken, and the cost of the process instances.

3.2 Analysis and Ranking Procedure

The analysis and ranking procedure commences once the process mining component has identified the various process models (variants) from the execution log. These are first grouped against behavioural similarity. We do not include this aspect in this paper due to space limitation and instead rely on the process proposed by Lu and Sadiq (2008). Then the *popularity* of the various variant (models) is determined by figuring the count of instances against each. Process popularity forms a benefit attribute. On the other hand, there is a cost attribute as well. We calculate this as the *weight* of the process based on time and resources utilized. Finally the cost and benefit attributes are combined through a multi-criteria decision making approach to identify the *best* process instance found from the history of instances within the execution log.

We first present some basic definitions in order to explain the analysis and ranking procedures.

Process Model. P is process model variance mined from the execution logs, where $P = \{P_1, P_2, P_3, \dots, P_n\}$. The architecture restricts that P are process models with variance which have the same goal. All process models are evaluated based on the behavioural dimension (Lu and Sadiq, 2008), as it contains the executional information such as the set of tasks involved in the process execution, the exact sequence of task execution, the performers and their roles in executing tasks, the process-relevant data, execution duration of the process instance and constituent tasks.

From the reconstructed process model, we have number of process instances captured by the execution log. A particular process instance will be represented as S, where $S = \{S_1, S_2, S_3, \dots, S_m\}$.

Definition 1 (Process Model Popularity). Let P_i denote the set of process model variants and S_j be the set of process model instances. Let $F(S_j, P_i)$ denote that *"S_j has the same process structure (behaviour) as P_i"* Thus process popularity R for a given variant i is

$$R_i = |S_j| \; where\; F(S_j, P_i), that\; S_j \text{ and } P_i \; are\; behaviourally\; similar \tag{1}$$

The popularity of the process model shows how many times a particular process (variant) models has been selected by user/used previously. A process matching on structural similarity (Lu and Sadiq, 2008) of business process model is used to identify the various (goups of) variant models discovered.

The best practice of business process will show the best alternatives from selected instances of process model. As it works with more than one criterion, a multi criteria decision making approach has been used to rank the alternatives.

Definition 2 (Process Weighting). Let S be the set of process instance. The weight ω represents the value (i.e. *cost value*) of an activity. Time needed to complete an activity is Δt. ω_{jl} is a value of an activity l of process instance S_j. Y_{jl} is the weight of an activity l of process instance S_j. Δt_{jl} is the time to complete an activity l of process instance S_j. We found that:

$$Y_{jl} = \Delta t_{jl} \times \omega_{jl} \tag{2}$$

Every instance S_j of process model will then have a summation of weight Z_j from activity A to m.

$$Z_j = \sum_{l=A}^{m} Y_{jl} + c \tag{3}$$

with c is some fixed value which is not related to the execution time (i.e. cost of resources such as to buy paper, etc).

Selected *top-k* of process model instances will be chosen from the set of process model instances with the least weights, where k is a maximum number of selected process instance defined by decision maker.

Definition 3 (Multi Attribute Decision Making). Generally the multi-attribute decision making model can be defined as follow (Zimmermann, 2001). Let $C = \{c_j \mid j = 1, \ldots, m\}$ the criterion set and let $A = \{a_i \mid i = 1, \ldots, n\}$ the selected set of process instance. A multi criteria decision making will evaluate m alternatives A_i $(i=1,2,\ldots,m)$ against C_j $(j=1,2,\ldots n)$ where every attributes are independent of each other. A decision matrix, X, given as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{4}$$

where x_{ij} is a rank of a process instance i against criteria j. The importance factor is given as W to show the importance relative of each criteria, where $W = \{w_1, w_2, \ldots, w_n\}$. This importance factor will be defined by the domain expert.

Definition 4 (Additive Weighting Method). The concept is to find the weighted summation of importance factor on each selected instances of process model (Fishburn, 1967). In order to compare all criteria, we normalise the *decision matrix X* into a comparable scale.

$$r_{op} = \begin{cases} \dfrac{x_{op}}{Max\ x_{op}} \text{ if } p \text{ is a benefit attribute} \\ \dfrac{\text{Min } x_{op}}{x_{op}} \text{ if } p \text{ is a cost attribute} \end{cases} \tag{5}$$

where r_{op} is normalised rank of selected instance alternative A_o against attribute C_p. Each selected instance will have a preferred value V_o, where

$$V_o = \sum_{o=1}^{n} w_p r_{op} \tag{6}$$

The preferred value V_o will indicate how we rank the selected *top-k* instances. The higher the V_o value is, the higher its rank among others.

Let us consider example from figure 1. From the execution log, we found variants of sequences *<T1, T2, T6, T5>*, *<T1, T3, T7, T5>*, *<T1, T2, T6, T7>*, *<T1, T2, T7, T8>*, *<T1, T2, T8, T7>*. Note that for a given process instance, there is exactly one execution sequence resulting from the execution, also having the same sequence does not guarantee two process instances could complete the process at the same time. The collection of execution sequences and counters (popularity) found from the process is shown in Table 1.

Table 1: List of all execution sequences S and their counters, from 100 process instances.

Sequences *S*	Count (S)
<T1, T2, T6, T5>	25
<T1, T3, T7, T5>	16
<T1, T2, T6, T7>	18
<T1, T2, T7, T8>	22
<T1, T2, T8, T7>	19

Table 2: Examples of collected instances.

Alternative *A*	Selected Instance *S*	Popularity *R*	Weight *Z*
A_1	S_3	25	150
⋮	⋮	⋮	⋮
A_8	S_{10}	18	149
⋮	⋮	⋮	⋮
A_{15}	S_{19}	19	146

The selected instances are named as alternative A, where $A = \{A_1, A_2, \ldots, A_n\}$. These alternatives are choices to be selected by the additive weighting method.

Weight is a cost attribute, as system will likely choose the least weight among all instances, while popularity is a benefit attribute, as system will prefer to use the most popular one. To get the decision matrix, we will normalise all attributes.

$$r_{11} = \frac{\min\{150;155;156;149;148;152;157;149;158;159;148;152;149;145;146\}}{150} = \frac{145}{150} = 0.967$$

$$r_{12} = \frac{25}{\max\{25;25;25;16;16;16;18;18;18;22;22;22;19;19;19\}} = \frac{25}{25} = 1$$

Subsequently we calculate the rests, and develop the normalised matrix as shown below

$$R = \left\langle \begin{matrix} (0.967,1.000), (0.935,1.000), (0.929,1.000), (0.973,0.640), \\ (0.980,0.640), (0.954,0.640), (0.924,0.720), (0.973,0.720), \\ (0.918,0.720), (0.912,0.880), (0.980,0.880), (0.954,0.880), \\ (0.973,0.760), (1.000,0.760), (0.993,0.760) \end{matrix} \right\rangle$$

The importance factor given by expert is $W = (6,4)$. The results are $V_1 = 6*0.967 + 1*4 = 9.80$; subsequently we will have $V_2 = 9.61$; $V_3 = 9.58$; $V_4 = 8.40$; $V_5 = 8.44$; $V_6 = 8.28$; $V_7 = 8.42$; $V_8 = 8.72$; $V_9 = 8.39$; $V_{10} = 8.99$; $V_{11} = 9.40$; $V_{12} = 9.24$; $V_{13} = 8.88$; $V_{14} = 9.04$; $V_{15} = 9.00$.

The EDRS output will highly recommend user to use the instance of alternative A_1 (S_3) to be used as it has the highest score relative to others against the given criteria.

4 METHOD EVALUATION AND CONCLUSIONS

Our study is not without limitations. Although the presented method does not seem to pose issues for efficiency as its computational complexity is low, the *Additive Weighting* process will require pair-wise comparisons which for a large data set can be prohibitive. Furthermore, when conflicting criteria in

the decision making framework are extended, it would lead a computationally hard problem.
In our future work, we hope to reduce the number of pair wise comparison in SAW method by incorporating emerging method applied in multi decision-making problem such as skyline query as proposed by Börzsönyi et al. (2001). We also plan to extend the criteria in the decision making framework with the help of empirical studies on real processes to gain the complexity faced in the real world problems.

In summary, this paper has presented a method for conducting business process analysis that aims at capitalizing on previous practices and experiences, thereby bringing about a *socialization of work practice* within an organization. The presented method balances costs (time and resources) and benefits (process popularity) by utilizing a multi-criteria decision making approach. Although we have used specific criteria to demonstrate the method, these can be extended to include further criteria to better reflect the requirements of specific process domains. Output from the recommendation service of ranked process instances can greatly assist the inexperienced user to utilize and learn from previous organizational knowledge and address specific cases with the knowledge of internal best practice.

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