Business Process Instances Scheduling with Human Resources Based on Event Priority Determination

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Abstract. Business Process Management (BPM) is concerned with continuously enhancing business processes. However, this cannot be achieved without an effective Resource allocation and a priority-based scheduling. These are important steps towards time, cost and performance optimization in business processes. Even though there are several approaches and algorithms for scheduling and resource allocation problems, they do not take into consideration information gathered from past process executions, given the stateless aspect of business processes. Extracting useful knowledge from this information can help achieving an effective instance scheduling decisions without compromising cost or quality of service. In this paper, we pave the way for a combination approach which is based on unsupervised machine learning algorithms for clustering and genetic algorithm (GA) to ensure the assignment of the most critical business process instance tasks, to the qualified human resource while respecting several constraints such as resource availability and reliability, and taking into consideration the priority of the events that launch the process instances. A case study is presented and the obtained results from our experimentations demonstrate the benefit of our approach and allowed us to confirm the efficiency of our assumptions.

Keywords: Business process, Instance scheduling, Priority determination, Genetic Algorithm, Machine Learning

1 Introduction

Business Process Management (BPM) is about "continuous improvement and optimizing process to ensure high performance by achieving agility and flexibility as a tool to gain competitive advantages" [1]. Most of the existing studies in BPM focused on maintaining and enhancing the process business logical correctness, or improving the process performance at both levels: build-time and run-time, by focusing on the optimization of process modeling issues at build-time and process scheduling issues at run-time. The process scheduling is considered as a crucial step in the journey of business process performance improvement, since there is an important relationship between the effective resource allocation and the business process improvement [2]. However, scheduling in general tends to become more complicated in near-real time systems. In general, business processes are different from scientific workflows as they may contain automatic tasks and non automatic tasks. Human resources are more difficult to manage as a human resource can execute other tasks that do not belong to the main process [3] or they may be available for only a specific time slots. Besides, several characteristics must be taken into consideration in order to choose the right human resource to execute a critical task (especially in critical sectors like health-care or banking), such as availability [3], competence [4], Seniority or reliability [5]. In this paper, we deal with a case of a process defined in an organization that can not control the arrival of tasks (online scheduling [3]), but at the same time it should maintain a balance between multiple constraints such as (priority, time, quality of service, lack of resources) to better manage resources and to minimize the overall execution time without compromising the quality of service. We only deal with human resources in this article. We address the challenges mentioned above with the following major contributions :

1- Business process instance priority determination based on the criticality of the events that launched these instances. In this step, we analyze the historical data from past business process execution using unsupervised machine learning algorithms for clustering to estimate the priority of incoming events and then the priority of the instances.

2- We propose a Genetic algorithm to solve our optimization problem which aims to achieve an effective assignment of the most critical process instance (result of the first step) to the most available human resource, while respecting several constraints such as resource availability and reliability.

The remainder of the paper is organized as follows. In the next section, we present an overview of related work to the problem of scheduling and human resource allocation in business processes. In the third section we introduce the objective and our context of work. Section 4 outlines our approach and methodology. Section 5 is devoted to the presentation of our experimental results and discussions. We conclude the paper in section 6 and we give an outlook on future work.

2 Related Work

This section will describe some of the related researches that have been done to solve the problem of scheduling and human resource allocation in business processes. Human Resource Allocation Problem (HRAP) is considered as a special case of assignment problem. S.Bouajaja et al. write a survey on human resource allocation problems [6], where they present the main approaches proposed in the literature to solve HRAP in different real life applications. Among these approaches, we find exact methods [7] or meta-heuristics [8]. But to deal with human resource allocation problem in the context of business processes and achieve an efficient resource allocation and scheduling in business processes, several approaches have been proposed in the literature. In order to ensure an effective and efficient resource allocation, authors in [9] present an approach based on association rule mining to extract and analyze rules about resource allocation from process event logs. In [10] authors focus on the integration of the priority aspect for human resource allocation in business process based on preferences. This approach provides also a mechanism for ranking resources. Another approach for resource allocation in business processes has been proposed in [11], where the authors tackle the problem of resource scheduling for several number of process instances by proposing two approaches based on heuristic rules to achieve a rational scheduling at build time and to take into consideration different dependencies that may exist between instances at run time. To the best of our knowledge, only few of these works present an effective instances scheduling based on event priority determination in incident management business processes. However, they do not take into account the stateless aspect of these processes, as such a process does not distinguish between events and it treats each event independently and without taking into consideration information that can be gathered from the previous executions. In the next section, we present in details the main idea and the problematic of this paper.

3 Objective and context of work

Each company must submit its business processes to a continuous improvement mechanism respecting their life cycle [12]. However, achieving a high level of enhancement cannot be done without integrating business process instances priority determination systematically with business processes improvement approaches. In fact, an optimized resource allocation based on instances priority ensures a positive impact on business processes performance, as it addresses time constraints and cost requirements without compromising the output quality. Some works on resource allocation focus more on changing and adapting the structures of the business process to better fit the resources available in the enterprise [2], others try to ensure an equitable sharing of resources between the different tasks or process instances [3]. Regardless of the adapted approach, managing efficiently resource allocation and time consumption could become a very important competitive advantage especially for organization where time and resources are crucial for their business improvement. Scheduling approaches in business process management take into consideration a lot of constraints related to instances of a business process, such as execution start time, finishing time and dependencies between tasks, in order to determine their priority. Despite this, instances of the same business process can still be executed in first in first out order, which hinder the efficiency of the service especially when one of these instances is launched by a critical event. Besides, this situation become more complicated when most of the tasks in this business process are executed by human resources.

3.1 Context of work and Motivation Example

The case study of our research work belongs to silver economy domain which is a new industrial sector officially launched in 2013 in France [13], in order to create personalized services and new technologies that are expected to improve disability-free life expectancy or to help dependent elderly people and their caregivers on a day-to-day basis. The risk of falls increases with age. In fact, losing physical capacities due to age or some kind of accidents can lead to serious falls of elderly people and those falls can have adverse repercussions. Let us consider a video surveillance company that edits an automatic falls detection system for elderly people and offers a 24/7 automatic alert solution and a quick rescue without the intervention of the person in danger. The incident management process used in this case study is based on a real-time analysis of alerts received from 24/7 streaming cameras for detecting elderly people's falls. This process is compliant to ISO 9001 corrective / preventive actions process. Besides, the global business process of this case study is simple but it represents several hard functional constraints such as: Business scaling, real-time data analysis and the obligation to maintain limited resources for the viability of the business. When an old person falls, the camera automatically detects it, takes a picture of the scene, and then saves the scene image and information about the event in a table in a data base. Those events are classified and qualified by human agents into 4 categories: False alerts (level 0): Empty place. False alerts (level 1): Active person. Alerts with average level (level 2): Seated person. High level alerts (level 3): Person lying down. The agent determines whether an assistance action is

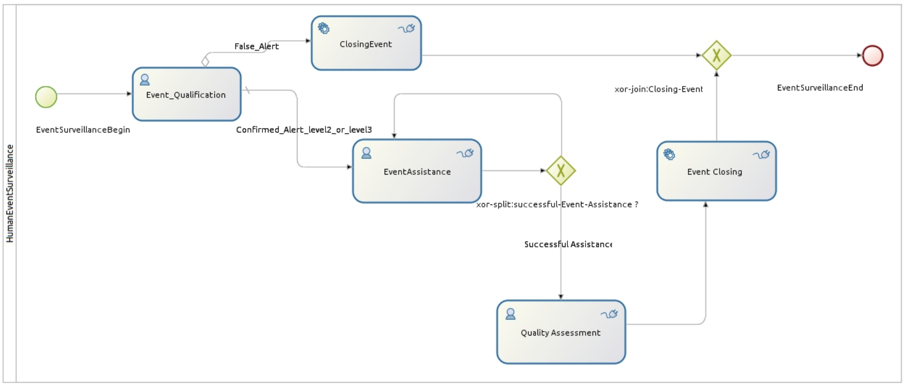

Fig. 1: Qualification and Assessment of the risk level of alerts Process

necessary or not (see Fig.1). That's why, each received alert (event) requires a quite vigilant treatment, in order to be sure of its category, because the margin of error in this type of system must be very small, as those falls, in case of a delayed intervention or an incorrect qualification, may have an adverse impact on the person concerned.

The growing needs of these type of companies (24/7 Streaming HD camera, increasing number of clients, unpredictable elderly people's falls), increase also the need to have more dynamic, adaptable and proactive business processes that ensure an appropriate responding to emerging customer events while maintaining an effective management of resources and without compromising one business process value (time, cost, quality, efficiency, flexibility, etc) over the other. It turns out that time and resources are the most critical values in these cases, and a non efficient management of resources preclude the organization from achieving an effective scheduling, and this consequently hinder the continuous improvement of these business processes. In the next section we present our approach that is based on genetic algorithm and clustering algorithm.

4 Approach and Model

We propose in this paper an approach based on two main steps to achieve a dynamic and flexible scheduling:

- Estimate the priority of several business process instances using an event priority determination approach: in this step we ensure a dynamic clustering for the events source using unsupervised learning algorithms. We attribute in fact the highest score to the cluster that contains the most critical cases. After that, each incoming event will be characterized by a score based on its cluster, so that the most critical event has the highest score. And then, the instance launched by the event that has the highest score has the highest level of priority.

- Assign the most critical instance tasks to an available human resource: in this step, we use Genetic algorithm to select the most suitable human resource and instance tasks matching, taking into consideration the availability and reliability of those human resources and the priority of each business process instance.

In figure 2, we schematize the ent-to-end process to achieve a priority and reliability based resource allocation for our approach.

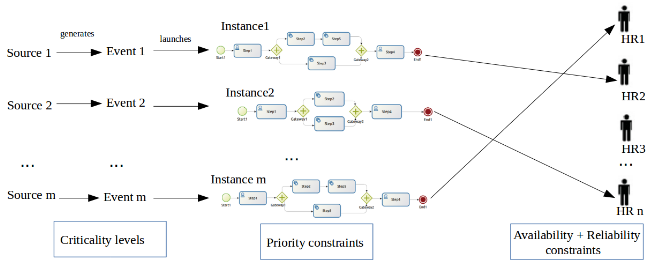

Fig. 2: Priority-based scheduling of process instances under human resource constraints

4.1 Definitions releted to business process scheduling problem

To understand the resource allocation problem in a business process, that we discuss in this paper, we need the following definitions:

Resource: r represents a unit that can be human or machine used to execute tasks of a business process. A resource must fulfill several constraints such as availability, execution time and cost, in order to be suitable for a specific task. In our approach we will take into consideration human resources only, and in general the number of human resources is finite and limited compared to machines. A is a set of agents (human resources), with n its cardinality.

Task: t is a logical unit of work in a business process that can be executed by a set of human or machine resources, depending on whether this task is automated or not. Time execution of each task depends on the allocated resource, so Time(t, r) represent the duration needed by a resource r to execute a task t. T is a set of tasks, with m its cardinality.

Business process: is a set of activities and tasks that exploit different resources to achieve one or more objectives. Business process is mostly characterized by a set of tasks and a set of resources.

Process instance: is a specific execution of a business process which is characterized by execution start time and execution finishing time for each task in this instance.

Resource allocation: is a matching between a task t of a process instance and an appropriate resource r.

Constraint: is a rule that control the execution tasks in a business process instance.

Priority: is a parameter used to choose between two or more tasks that need the same resource at the same time. The lowest priority task must wait for the resource occupied by the highest priority task.

4.2 Formulation of priority-based business process scheduling problem

The main objective of our approach is to ensure an effective and optimal human resource allocation and instances scheduling, while respecting the following constraints:

- Priority of a process instance: the priority in our approach depends not only on the execution time interval, but also on the criticality of the event that triggers the instance.

- Availability of human resources: in our approach we have two type of availability: The initial availability, which is related to SLA (Service-level agreement) between the hired human resource and the company. And the availability at time t, which is related to whether a human resource is assigned to execute a task or not. To determine the time that a human resource will spend to execute the allocated tasks in order to determine his availability, existing approaches proposed several methods to estimate the available time slot of each resource based on the time that a specific task require to be executed. However to gain more flexibility and to ensure a real time service we propose in our approach to manage the availability of each human resource using an online system that shows whether a specific human resource is available to receive a new task or he /she is not available (absent or allocated to an other task).

- Reliability R_i of each human resources r_i: Since we are dealing with an incident management business processes, the error rate must be very small especially for the critical tasks. That's why, we include this metric which is calculated based on the number of errors that a specific human resource has made in a determined time interval.

$$Reliability = \frac{1}{\sum_{j=1}^{k} P_j N_j} \tag{1}$$

with P represents a weight which is proportional to the criticality level of the event. And N represents the total number of errors a human resource has committed while qualifying previous events, for each criticality level k.

The objective of our model is to minimize the total cost-reliability ratio for all available human resources. While respecting the constraints in order to ensure that a human resource can be assigned to one task at a time, but we must also respect the human resource initial capacity and also his/her availability in order to assign to them only tasks that occur in their availability time slot.

$$min \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{C_{i,j}}{R_i} x_{i,j} \quad (2)$$

Subject to

$$\sum_{i=1}^{n} x_{i,j} = 1, j = 1, ..., m \quad (3)$$

$$\sum_{j=1}^{m} a_{i,j} x_{i,j} \leq Init\_Availability(r_i), i = 1, ..., n \quad (4)$$

The objective function represents the cost-reliability ratio, where c_{ij} represents the cost of the allocation of human resource r_i to task t_j, and R_i refers to the reliability of each human resources r_i (equation 1).

x_{ij} in the first constraints, represented by equation (3), represents the decision variable ($x_{ij} = 1$ if human resource r_i is allocated to execute task t_j; 0 otherwise). This constraint means that each task is assigned to only one human resource. In equation (4) a_{ij} represents the total time used by the human resource r_i when assigned to execute a task t_j, and this equation means that the total time used by each human resource cannot exceed his/her initial availability.

4.3 Event priority determination Step

As mentioned previously, in order to schedule our business process instances according to their priority, we estimate this priority based on the criticality of the events that launch those instances. We proceed to a dynamic clustering in order to score and to estimate the priority of the incoming event based on the cluster of its source.

We opted for clustering algorithms to discover groups in our dataset, we choose K-means clustering algorithms and we tested several criteria such as the frequency of falls or total number of falls, in order to have the most representative clustering for our data. We apply K-means algorithm on a set of events sources in order to classify those sources on different clusters using a score that we calculate for each event's source (a patient in our case) based on the frequency of previously generated events and their criticality value given previously by the agents (human resources) in the qualification step (see Fig. 1). This first step of our proposed method uses basic iterations of K-means algorithm. The event criticality is ranged from low level (0) to very serious (3), and there is a bijection between event criticality levels and instance priority. Two scenarios are encountered when applying this approach:

1- The sources of the incoming events belong to different clusters: in this case, the score of each cluster helps us to determine the criticality level of each event, which help us to estimate the priority level of the business process instance launched by this event. So, the instance launched by an event thet was generated from a source that belongs to the critical cluster has a higher priority than the other instance.

2- Both sources, that generate the events, belong to the same cluster : in this case, the criticality level of each event is determined by the comparison of the score (used to cluster the sources) of each event source.

4.4 Instance Tasks and Resource matching Step

Meta-heuristics present a potential solution for scheduling problems when exact methods are unable to find an optimal solution within a reasonable computational time [6]. Genetic algorithm is a meta-heuristic that has been proposed in 1975 by John Holland, it belongs to evolutionary algorithms group, and it aims to solve optimization problems by simulating the intelligence of natural selection and genetics [14] following specific steps as shown in this pseudo-code:

Algorithm 1 Genetic algorithm

```
Begin
1: Randomly generate an initial population of different individuals
2: Evaluate the fitness of each individual of the population
3: repeat
4:     Select two parents from the population
5:     Generate offspring by the selected parents
6:     randomly Mutate the offspring
7:     Evaluate the fitness of the offspring
8:     Replace the less important individuals in the initial population by the best ones
       from the offspring
9: until convergence criterion is met // time limit or specific number of iteration
```

The use of a meta-heuristic in our approach is intuitive as we are facing an optimization problem, and meta-heuristics have proven their efficiency and their capability to obtain near-optimal results, through several works previously done by researchers. But we opted for Genetic algorithm instead of other meta-heuristics such as Artificial Bee Colonies algorithm (ABC) or Ant Colony Optimization algorithm (ACO), as it was more adaptable to our case. Besides the phases of GA offer more flexibility in order to propose modified or adapted algorithm versions by researchers, for example [15] [16]. In fact, we proposed also in this paper an adapted version, of genetic algorithm previously described, to our approach. Our optimization approach consists on of the following phases:

Input parameters and Population initialization Like other population-based search and optimization algorithm, the initial phase of genetic algorithm starts by generating the initial population and set the initial parameters. A population in genetic algorithm (GA) represents all the possible solutions for the problem, and an adequate representation of a population of candidate solution increases the efficiency of GA results. For our approach, each individual from the initial population is encoded as vector where the first element of this vector represents the human resource index and the second one represents the task index. An individual in our case is represented as possible one-to-one matching between a human resource and process instance tasks. So our population will have the following representation (see Fig. 3).

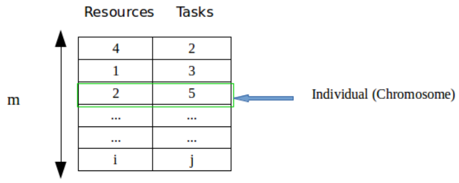

Fig. 3: Representation of population of candidate solutions

Population fitness-based evaluation As we mentioned before, our purpose is to ensure one-to-one matching between a human resource and process instance tasks. We evaluate the fitness value of each individual in the population. This fitness represents the total cost-reliability ratio of the available human resources that will be allocated to the current tasks (see equation. 2).

Parent Selection and Population reproduction In this phase, the individuals of the initial population (parent) are sorted based on their fitness values. Among the different selection technics in literature (Tournament Selection, Roulette Wheel Selection, Rank Selection, ...), we apply rank selection. This technic consists on sorting the individuals by their fitness score and after that we randomly choose the parents from the individuals with higher ranks.

Crossover phase is a step in genetic algorithm which consists on selecting two random individuals (chromosomes) and switch between their elements (genes) to generate a new population. In our approach, we can only use the one point crossover strategy to the individuals of our population given their representation (see Fig. 3).

Mutation phase and New generation is an operation in genetic algorithm that consists on randomly modifying an individual. In our case, we opted for selecting the first element of the individual (chromosome) which represents the human resource index and modify it with an index of another available human resource. To obtain the future population we use the "Elitism" with a fitness based selection approach, which consists on keeping the fittest individuals of the current population, and those individuals replace the least fit offspring in the new generation.

Termination Condition Time is a crucial factor in our case study, since we are dealing with critical events (falls of elderly people). So we use time as a limit condition.

5 Experimental Results and Discussions

In the following, we present a summary of the results obtained from our experiments, in order to demonstrate the effectiveness of the combination of the two proposed approaches. All our experiments were conducted on an Intel(R) Core(TM) i5- 540M 2.53GHz.

For the first step in our proposed approach, which aims to estimate the priority level of each business process instances based on the criticality level of each incoming events that launch these instances, we used K-means algorithm that we coded in R language. For this, we took a dataset of patients falls over the period from 01-02-2016 to 12-06-2017, this dataset is consisted of 238228 observations generated by 81 patients: 89312 alerts are of level 0 (low), 148466 of level 1(average), 275 of level 2 (serious) and 175 of level 3 (very serious). This dataset represents historical data gathered from our previous business process past instances (see Fig. 1). As shown in (fig. 4), we obtain four clusters with the K-means algorithm based on the score of each patient calculated using the total number of his/her falls, taking into consideration level 2 and 3 only.

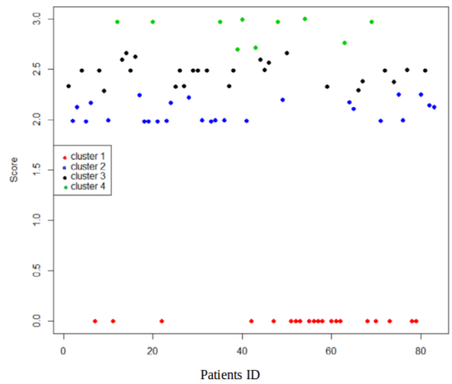

Fig. 4: Clustering of patients based on their score

Analyzing the historical data of each patient, helped us to cluster the patients into categories and find similarities between different patients. Each time a new event has been processed, the clustering is dynamically restarted in batch to ensure that the clusters are continuously updated and conclusive regarding the evolution of the patients health level. In fact, this helps us to keep the score and the cluster of each patient updated in our database since we are using these two criteria to estimate the priority of the incoming events, in order to execute the instances linked to those events in priority order instead of first in first out order, as shown in the (fig. 5). The first part of this figure represents the contents of the Json file that we send to our API (Application Programming Interface) in order to sort the incoming event by priority using the score and the cluster ID of each patient. The second part of this figure shows the received results. As we can see the score obtained for each event corresponds to the result of our clustering, and those events are sorted based on the score and the cluster ID of their sources.

In the second step, which represents the human resources allocation step in our approach, Genetic algorithm and all other algorithms were coded in Java programming language. To experiment our Genetic Algorithm based approach for human resources allocation we used 8 human resources (see Table 1) with the same sorted events from our first experiment (see Fig. 5). The results obtained from this matching operation (Resource, Task) respect the two constraints that we propose in our approach which are the reliability score and the initial availability which is linked to the time slot of availability for each human resource. We obtain the following result (7, 88876), (1, 88875), (2, 88874), (5, 88873).

(a) Received events (b) Sorted events

Fig. 5: Event priority determination

Among the available human resources, Only the ones with high reliability score were selected.

Table 1: List of humain resources

Human resource ID	Reliability score	Initial availability	Time slot of availability
1	0.13	4 hours	8AM - 12 (Noon)
2	0.20	4 hours	8AM - 12 (Noon)
3	0.25	8 hours	2PM - 8PM
4	0.19	3 hours	2PM - 5PM
5	0.57	4 hours	8AM - 12 (Noon)
6	0.31	4 hours	4AM - 8AM
7	0.12	2 hours	10AM - 12 (Noon)
8	0.43	6 hours	6PM - 12 (Midnight)

In addition to the constraints related to human resources (availability and reliability) and to business process instances (priority), response time is also an important criterion that we should take into consideration in our approach since we are dealing with a critical tasks that should be allocated to human resources in near real-time. For this, we conduct another series of experiments in which we keep a fixed number of human resources, but we have modified alternately the number of tasks and the number of generation that we used within our genetic algorithm. The following figure (Fig. 7) represents the obtained results.

We observe that our priority based scheduling approach allows us to schedule up to 20 events in just a few seconds. Increasing generation number causes a slight increase in processing time, but the final result of resource allocation is the same. Thus we have limited the number of generations in our Genetic algorithm to 50.

6 Conclusion and Future Work

In this paper, we introduced a two-phase approach to ensure an effective scheduling in the case of critical tasks that must be executed by human resources. The first phase represents a solution for event priority determination to ensure an effective instance scheduling in business process. This solution is based on the

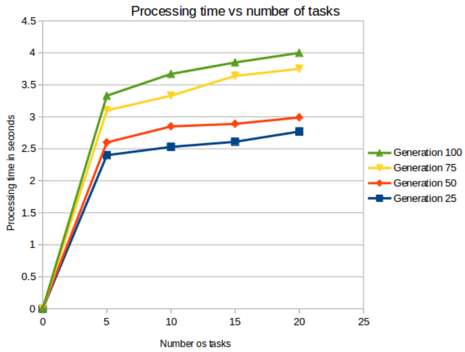

Fig. 6: Variability of the processing time according to number of tasks and number of generation

analysis of historical data from past business process execution using unsupervised machine learning algorithms for clustering, in order to manage the priority of several events that launch business process instances. The second phase is about resource allocation. In fact, the problem of scheduling in business processes, has several constraints at the same time such as resource availability and reliability, and time. As this problem is considered as an optimization problem, we propose a genetic algorithm to solve it in order to achieve an effective matching between the most critical process instance and the most available human resource. Our solution ensures that the events are processed according to their order of priority, by exploiting the result of our clustering step to estimate the criticality of the incoming events. In our future work, we project to improve our approach by introducing other technics to provide a real-time scheduling in business process management.

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For privacy management, all data has been anonymized.

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