Human-Resources Optimization & Re-Adaptation Modelling in Enterprises

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ABSTRACT: Optimization of Human Resources (HR) and re-adaptation are of vital importance to enterprises in order to keep the workload balanced and maintain high performance levels when unexpected events or exceptions occur, such as an arrival of a new unscheduled task. In this paper, a novel HR optimization & re-adaptation model for enterprises is introduced. The model integrates different entities such as employees, processes, work schedules, resources, and location information. The heterogeneous information is translated to a common vocabulary in order to be utilized for assigning tasks to human resources automatically without the need of supervision. Conditional Random Fields (CRFs) probabilistic models are trained, so as to learn the already applied task assignment patterns, and their output is taken into account in the decision process. The HR optimization toolkit, which comprises the models and the HR optimization tool, has been tested with real data acquired from an industrial environment achieving favourable results towards HR assignment.

1 INTRODUCTION

Resource management is crucial for the performance of an enterprise. Efficient management of resources in enterprises, and especially in dynamic environments such as shop floors, is a great challenge as various factors have to be taken into account in order to deal with possible unexpected events. Examples of such real-time events include machine failures, arrival of urgent jobs, due date changes, changes in job processing time, etc. (Varela & Riberio 2014). The goal is to achieve the optimal management of the resources according to the current condition and based on the preferred policies.

The two main types of resources that have to be managed in enterprises are machinery resources and human resources. These resource types have different characteristics. Machines are subject to unexpected failures and their performance is characterized by low variability. On the contrary, the performance of an employee when executing a task depends on various parameters such as the experience level, skills, time of the day etc. Furthermore, workload balancing among employees is vital to ensure fairness and employee convenience.

A resource assignment algorithm deals with the assignment of resources by selecting the most suitable from the ones available and by taking into account resource constraints. On the other hand, a scheduling algorithm assigns resources to tasks while setting the execution starting time of tasks as well. The present paper focuses on the first problem category. Depending on the execution phase, resource allocation can be static or dynamic. In the former case a set of tasks and a set of resources are available at design time and the allocation of resources is decided before the execution starts. Contrariwise, dynamic resource allocation is performed when a new task arrives at run time.

Due to the high interest in task scheduling and resource assignment, there are several studies in the literature proposing various approaches to deal with the above-mentioned problems in the context of human resources. References of recent work on personnel assignment and human resource scheduling are provided in the following two paragraphs, respectively.

Wibisono et al. (2015) propose an on-the-fly dynamic human resource allocation method in Business Process Management Systems which is based on Naïve Bayes model. The results showed that their approach outperformed other rule-based methods applied, such as Random and Order-based. A mechanism in which the dynamic resource allocation optimization problem is modelled as Markov decision processes is proposed by Huang et al. (2011). The mechanism observes its environment to learn appropriate policies which optimize resource allocation in business process execution. An alternative approach presented by Liu et al. (2008) applies a machine learning algorithm (decision tree, Naïve Bayes, SVM) to the workflow event log to learn various kinds of activities that each employee undertakes. When staff assignment is needed, the classifiers suggest a suitable actor to undertake the specified activities. The approach is characterized by the authors as semi-automated because the workflow initiator needs to make the final decision. Another interesting solution for the human resource assignment problem is proposed by Cabanillas et al. (2013), where the authors specify and utilize a metamodel to define preferences. In that work the human resources are prioritized according to preferences, based on a ranking mechanism.

Recent work on the NP-hard complex resource scheduling problem includes approaches based on multi-agent systems and heuristics. More specifically, Skobelev et al. (2013) have proposed an adaptive scheduling method for resource management in manufacturing workshops, which is based on a multi-agent system. The system's model includes agent classes such as Order, Worker, Machine and other. Agnetis et al. (2014) propose two heuristics (STA-OMSB, MSB-DOS) that solve job shop scheduling problems in handicraft production, taking into account also the skills of each employee. The case study that was examined revealed that the MSB-DOS method yielded close-to-optimal solutions in reasonable time. Lastly, Bouzidi-Hassini et al. (2015) discuss a new approach to integrate the scheduling of production and maintenance operations. The approach takes into account human resources availability and is based on multi-agent systems for modelling the production workshop. However, the allocation of activities to the best human resource based on its competence is not considered.

This paper presents a novel model for Human Resource optimization in enterprises. Various static and dynamic parameters of the involved entities such as tasks and employees are incorporated and combined. The model definition allows a monitoring component to assess the operational status of the enterprise in real-time and respond to changes regarding the workload. By using the defined model, multiple criteria such as the workload and task priority can be taken into account for assigning human resources to tasks automatically. Furthermore, (a) Conditional Random Fields probabilistic models (Sutton & McCallum 2006) are trained and employed in the resource selection process and (b) the use of thermal cameras for extracting the location of employees is examined. The components of the system and its architecture are also presented.

The remainder of the paper is organized as follows: Section 2 presents the HR model and the HR assignment method applied. Section 3 describes the architecture of the HR optimization toolkit and section 4 presents case study results. Lastly, conclusions and future directions are summarized in section 5.

2 PROBLEM DESCRIPTION & MODELLING

2.1 *Problem description*

The primary goal is to build a HR model for use in enterprises. The model has to be as generic as possible and be extendable with additional parameters or entities. The latter is important since operations and requirements in an enterprise may change over time. The defined model is utilized by an HR optimization component which helps to automate and optimize the HR assignment process in static or dynamic resource allocation, and to provide the manager with visualized information about the progress of task execution.

The manual assignment of urgent tasks to employees by the manager or the supervisor can be time-consuming. Thus, in order to deal with this issue, the primary objective is to automatically select the most suitable employee(s) to perform an arriving task, by taking into account multiple criteria in real-time. The HR model includes all the necessary information used as input for making the final decision, such as the current work schedule per employee and other information about the current state.

2.2 *HR model description*

The HR model is a bridge between the HR strategy and other key areas of HR management, such as processes, actors, etc. The model adopts entities and the vocabulary of Business To Manufacturing Markup Language (B2MML). B2MML (MESA XML Committee 2013) consists of a set of schemas written using the XML Schema language (XSD) that implement the data models in the ISA-95 standard. Furthermore, in addition to the B2MML schemas, new XSD schemas have been defined regarding the format of sensor information, measurements and localization.

BIMs (Building Information Models) are digital representations of physical and functional attributes of infrastructures such as houses, factories etc. (Azhar 2011, Volk et al. 2014). A Building Information Model (BIM) which contains the locations of critical assets and equipment is utilized by the HR model. BIM information is extracted and stored in gbXML format. In this way, the layout of the facility along with the positions of critical equipment and employees can be visualized and presented to the manager.

The two main entities employed in the HR assignment modelling are the human resources (employees) and the tasks. A task T can be atomic or composite. A composite task CT is composed of $k>1$ atomic tasks (T_i. i = 2, 3, …, k). Composite tasks or processes are common in enterprises operations and are usually represented by directed graphs, where each node is an atomic task. The execution order of tasks in a process has to be defined in addition to the number of employees required per each trade. To this end, additional properties for each task belonging to a *CT* are defined, such as the ID of the *CT*, flags showing whether the task is the first or the final in the *CT*, and a set of the IDs of the preceding tasks. The definition of these properties allows us to model different types of workflows, such as workflows that include only sequential tasks or workflows that include tasks that can be executed in parallel. The properties of tasks that are utilized in the assignment process are listed below:

– ID
– Employee trade required
– Number of employees required
– Estimated duration in minutes
– Scheduled starting time
– Priority weight
– Location
– Assets required

The specification of task information utilized by the HR model, such as the qualifications of employees required, is the result of job analysis (Morgeson et al. 2004). Job analysis provides information to enterprises which helps to determine the best fit employees for specific tasks. Prototypes of the common tasks occurring in the enterprise are built and are part of the model. Each task prototype defines the static parameters of the task and can be identified by its unique ID number. The availability of the characteristics of common tasks facilitates the automated creation of new tasks in the system when emergency events, such as critical malfunctions, are detected. Each task usually requires an employee with specific trade e.g. a technician and therefore it cannot be performed by an employee of a different trade. We also assume that an estimated duration of each task in minutes is also known. It can be the average execution time of past instances of the task. For each already scheduled task, it is expected the starting time of the task to have been defined. For new urgent tasks we consider that the scheduled starting time is also defined (as the task starts shortly after the arrival). Priority weight denotes the level of importance of the task and is a real number in [0…1]. The approximate location of the task is the name of the area where the task is performed. Placement information is retrieved from the BIM. Assets (e.g. machines, spares) required by a task are considered as constraints in HR optimization.

The static and dynamic properties of employees are listed below:

– ID
– Hierarchy scope
– Trade
– Experience level
– Shift starting/ending time
– Current Position as X,Y coordinates
– Work schedule
– Running task

The trade of the employee denotes his/her expertise. An employee can have more than one trade. The experience level is also defined per each employee (Trainee, Novice, Experienced). The HR model supports preemption. As a human resource can be regarded as a processing unit which processes tasks, preemption means that a task being performed by an employee can be temporarily interrupted and resumed at a later time. This property allows an employee to execute a new task of higher priority shortly after its arrival. In this work we assume that all the employees working at each time instance share common starting and ending shift times. Table 1 below summarizes the most important parameters utilized in the proposed HR model.

Table 1. Main parameters of the HR model.

Parameter	Employee	Task
ID	Yes	Yes
Trade	Yes	Yes
Location	Yes	Yes
Work schedule	Yes	–
Estim. duration	–	Yes
Starting time	–	Yes
Priority weight	–	Yes

2.3 *Towards HR localization using thermal cameras*

In order to support the real-time localization of employees, a method for calibrating thermal cameras against the BIM, which is used as reference point, has been developed and evaluated. Thermal cameras are utilized offering notable advantages in respect to other imaging systems. They have gained popularity over the past few years, since they yield good results under adverse illumination conditions. This renders them particular popular for both indoor/outdoor monitoring applications. Moreover, their performance is not greatly influenced by shadow effects or other physical limitations that might be encountered in uncontrolled enterprise environments due to the presence of smoke, gas, increased humidity, etc. For thermal camera's geometric calibration, a calibration pattern was manufactured and prepared, exhibiting high-thermal contrast. A ray-tracing approach against the shop floor's geometry, obtained through the BIM, is performed in order to produce a detailed 3D thermal model. Each surface can be projected on a parallel plane (orthographic projection), resulting in images with geometric scale and no distortion, called orthothermograms. The proposed approach enables an end-to-end camera pose estimation and that allows spatially accurate motion detection and indoor monitoring for employee localization within the shop floor (Fig. 1). Information extracted from the thermal cameras can be fused with RFID or another similar technology in order to identify with improved accuracy an employee's position within the inspected area.

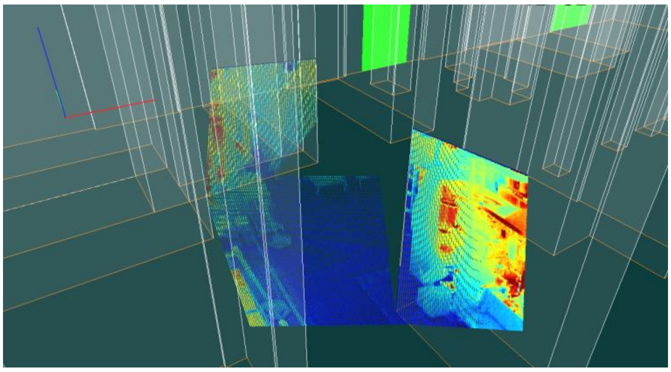

Figure 1: 3D thermal model of the inspected area.

2.4 *HR assignment method*

The proposed dynamic HR assignment method, which utilizes the HR model presented in the previous sections, ranks the candidate employees and then selects the required employee(s) for a task. The higher the ranking of an employee, the lower the assignment cost is. One of the factors that affect the assignment cost of employees is derived from the output of Conditional Random Fields (CRFs) probabilistic models. The probabilistic models incorporate the enterprise's practices as they are built using historical task assignment examples. However, since these past task assignments may not be the optimal, additional criteria are also considered for ranking the candidate employees. A CRF model is created per each employee. The main advantage of a CRF when compared to a Hidden Markov Model (HMM) is the ability to include more complex non-independent features of the observations. The probability of producing a state sequence *y* given an observation sequence *x* can be computed by Equation 1 below:

$$p(y|x) = \frac{1}{Z(x)} exp\{\sum_{k=1}^{K} \lambda_k f_k(y_t, y_{t-1}, x_t)\} \quad (1)$$

where f_k = feature function; λ_k = learned weight associated with feature f_k; and Z(x) = the normalization function shown in Equation 2.

$$Z(x) = \sum_y \exp\{\sum_{k=1}^{K} \lambda_k f_k(y_t, y_{t-1}, x_t)\} \quad (2)$$

At each time step, the model takes as input a feature vector (observation) and infers the hidden state. The estimation produced at each time step is the model's hidden state and in our case it can be either 0 (not recommended for assignment) or 1 (candidate for assignment). The feature vector constructed at each time step comprises the following features, normalized to [0…1]:

1 the type (ID) of the arriving task to be assigned
2 the employee's conformance to the trade required by the task
3 the employee's remaining workload level

The use of the task type in employees models favours the selection of employees with frequent past assignments of the particular task. The particular behaviour is desirable since these employees tend to be more familiar with the task resulting in high execution performance. The second feature denotes if the employee is able to perform the task. In case the trade does not match with the trade required, its value is 0. Regarding the employee's remaining workload, five different levels are possible (None, Low, Medium, High, Max). It is computed based on the estimated durations of the employee's scheduled tasks.

A training phase is required in advance in order to create each CRF model. A sequence of observations along with the actual ground truth label per each observation must be provided as input for learning the model parameters per each employee. The training data per model are created concurrently for all employees by using historical assignment events in the form: < *Time, TaskID, EmployeeID* >.

The total selection cost for each employee E is computed as follows:

$$E_{totalcost} = (1 - W) \times E_{cap\_cost} + W \times E_{adapt\_cost} \quad (3)$$

where W = weight factor set to 0.6, E_{cap_cost} denotes the capability cost and E_{adapt_cost} denotes the adaptation cost. They are computed respectively by the two equations below

$$E_{cap\_cost} = W_1 \times E_{model\_cost} + W_2 \times E_{rem\_wload} + W_3 \times E_{dist} \quad (4)$$

where $W_1 + W_2 + W_3 = 1$.

$$E_{adapt\_cost} = (E_{overlap} + E_{weight\_comp} + E_{task\_inter})/3 \quad (5)$$

Each CRF model's current belief probability (bp) of being in state 1, which is a real value in [0…1], is retrieved. E_{model_cost} is derived from the belief probability (bp) of the employee's CRF probabilistic model and is equal to 1-bp.

E_{rem_wload} denotes the normalized remaining workload of the employee until the end of the shift. It is computed by dividing the total duration of remaining work in minutes by the total minutes left until the end of the shift. Remaining workload is an important parameter and considered in both the probabilistic model and the cost function. Only considering employee capabilities during task assignment may result in most capable employees being assigned a heavier workload (Shen et al. 2003).

The current location of employees can be taken into account for selecting the employee who is closer to the location of the task in order to improve responsiveness. The normalized distance cost factor

(E_{dist}) is the Euclidean distance between the task location and the employee position divided by the maximum possible distance that can be observed based on the architectural plan derived from the BIM model.

$$E_{dist} = \frac{\sqrt{(E\_x - T\_x)^2 + (E\_y - T\_y)^2}}{\max\_distance} \tag{6}$$

The cost factors in the employee capability equation are not of the same weight. Instead, the weight values depend on the selected assignment policy mode, which can be either ‘Performance’ or ‘Balancing’. Thus, when operating under the ‘Performance’ policy $W_1 = 0.5 > W_2 = 0.3$ and when operating under the ‘Balancing’ policy $W_1 = 0.3 < W_2 = 0.5$. The policy can be selected by the manager.

In order to compute the adaptation cost, a check is performed for determining whether the arriving task overlaps the employee’s running task or a scheduled task. If this is not the case (the employee is available for the whole specific time period), then $E_{adapt\_cost} = 0$, otherwise the list of overlapping tasks is returned. $E_{overlap}$ is defined as the ratio the arriving task is overlapped (based on its scheduled starting time and estimated duration) by the employee’s running and scheduled tasks. E_{weight_comp} cost factor takes into account the priority weights of the tasks. The priority weight of the arriving task is compared with the weights of the overlapped scheduled tasks. $E_{weight\_comp} = 1$ in case the arriving task’s weight is lower than the weight of at least one overlapped scheduled task. The task interruption cost (E_{task_inter}) equals to the elapsed execution time of the currently running task divided by its estimated duration. This factor implements the concept of introducing cost proportionate to a running task’s remaining execution time. The motivation behind this factor is to declare that it is undesirable to interrupt a task with short remaining execution time.

In case of insertion of an unexpected task into the work schedule, the execution of an already scheduled task may not be able to be started on time because of employee unavailability due to time overlap. Therefore, a check is performed in order to examine if the affected task can be postponed by advancing the scheduled starting time without introducing new overlaps (re-adapt the employee’s work schedule). If this is not the case, a strategy has to be defined for determining the remaining tasks that have to be rescheduled.

The steps of the HR assignment method are presented schematically in Figure 2.

3 SYSTEM ARCHITECTURE

The HR optimization toolkit comprises the models, the localization component and the HR optimization component. All information is available through APIs and a shared common vocabulary is defined. The middleware is responsible for the distribution of information. Furthermore, all information of the HR model is stored in its database.

The localization component is responsible for the extraction of the positions of employees in the enterprise premises. As such, the location of each employee at each time instance is sent to the HR model for storing and distribution.

The HR optimization component executes the HR assignment in case a new task has to be performed. Moreover, it analyses the work schedules and monitors the execution progress of tasks. Thus, possible exceptions that can affect both the current work executed and the scheduled future work can be detected. The supervisors and the manager can be notified about an exception in order to take appropriate actions.

The management application is used by the manager and runs on a desktop PC. The manager can review the current progress of tasks and access information such as the completed tasks and the availability of each employee. New tasks can be also added to the system through the management application.

Each employee is able to view the daily work schedule and his scheduled tasks by using a mobile device. Upon an assignment of a new task, the employee is notified accordingly. Moreover, the employee declares the actual starting time and ending time of each task he/she performs. The system architecture is depicted in Figure 3.

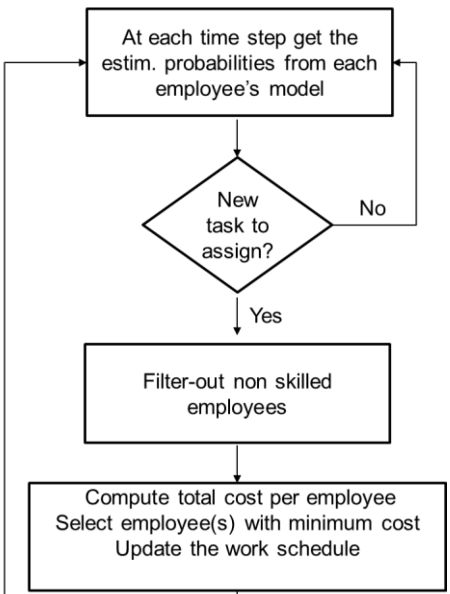

Figure 2: Steps for HR assignment.

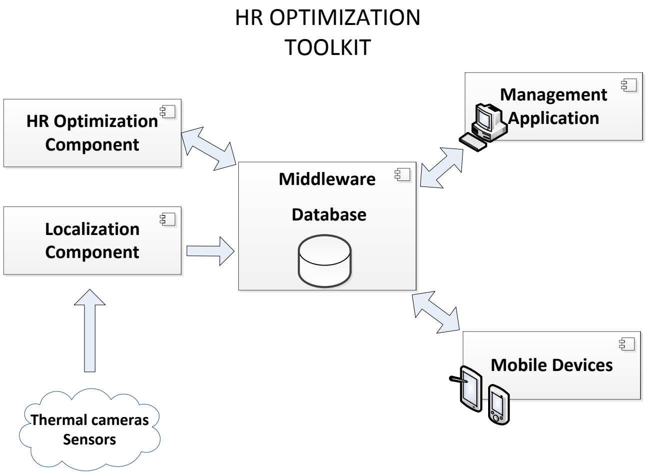

Figure 3: System architecture.

4 CASE STUDY

In order to test the functionality of the HR optimization toolkit, real static and dynamic data were acquired from an industrial shop floor for chemical processes. Information about different tasks, information about employees and historical data were embodied in the HR model. The HR resource assignment algorithm was run in offline mode under different initial state cases.

The specific shop floor involves employees of different trades such as process operators, maintenance supervisors and technicians. Automation, Electrical and Process technicians are the main distinct technician trades employed. An excerpt from the definition of employee static information in XML format is illustrated in Figure 4. The scenarios that will be presented concern the assignment of Automation technicians. More specifically, the case study is about a maintenance composite task (replacement of a heating resistance) of high priority with estimated duration of about 150 minutes that has to be assigned and executed as soon as possible. One Automation technician is required (along with employees of other trades) and must be selected from the two candidates Automation technicians (ID1: 14-NM, ID2:18-PK) who are present. The scheduled starting time of the maintenance task is 10:06 a.m.

4.1 *Experimental results*

In the first scenario, which is the most straightforward, there is not any scheduled or running task during the time interval required by the arriving task for neither of the two candidate employees. Therefore, both technicians are available, no task overlap exists and the employee adaptation cost E_{adapt_cost} = 0 in both cases. As it is illustrated in Figure 5, the technician with ID 14-NM has two scheduled tasks in his work list: the first one has an estimated duration of 3 hours while the second one lasts 30 minutes. On the contrary, only a 3-hour task is scheduled to be performed by the technician with ID 18-PK. Eventually the latter Automation Technician was selected for the task, yielding the lower cost, which was 0.167 as opposed to 0.182 for 14-NM technician, due to the lighter remaining workload.

In a second scenario employing the same technicians, which is illustrated in Figure 6, the already assigned task of each employee overlaps with the arriving high priority maintenance task. Moreover, the technician with ID 18-PK is performing another task which has started at 09:15 when the high priority task arrives. Thus, the adaptation cost E_{adapt_cost} of technician 18-PK is much higher (0.533 versus 0.034) due to the longer overlap ratio and the need to interrupt the currently running task which is about to finish soon. The total cost E_{total_cost} calculated for technician 14-NM is 0.203, which is lower than the cost that corresponds to technician 18-PK (0.491). As a result, technician 14-NM is selected in this case even though his remaining workload is higher. We have to note that in both cases tested, the estimations produced by the CRF models were almost the same for both technicians (1 versus 0.99) and as a result the respective cost factors were negligible.

In both the aforementioned scenarios, the applied assignment policy for calculating E_{cap_cost} was set to 'Balancing'. We also have to note that distance computation was not utilized in the case study since employee location information was not available. The installation of the equipment required for the localization of employees is a work in progress.

```
- <Actor>
    <ID>13</ID>
  - <Description>
      Handles mainly tasks regarding electrical malfunctions on pilot plants
    </Description>
    <HierarchyScope>Operators and Technicians</HierarchyScope>
    <Category>Users</Category>
    <GroupName>Electrical Technician</GroupName>
    <ExperienceLevel>Experienced</ExperienceLevel>
  </Actor>
- <Actor>
    <ID>14</ID>
  - <Description>
      Handles all malfunctions ragarding the automation equipment at the shop floor
    </Description>
    <HierarchyScope>Operators and Technicians</HierarchyScope>
    <Category>Users</Category>
    <GroupName>Automation Technician</GroupName>
    <ExperienceLevel>Experienced</ExperienceLevel>
  </Actor>
```
Figure 4: Static information about employees (actors) in XML format.

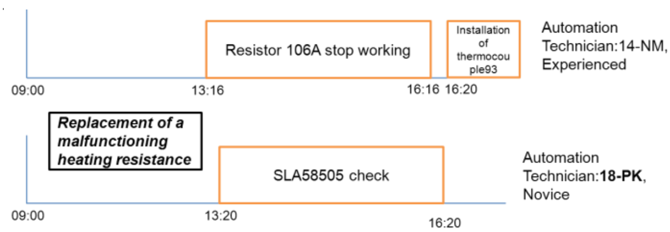

Figure 5: Assigning a technician to an arriving task according to the first scenario.

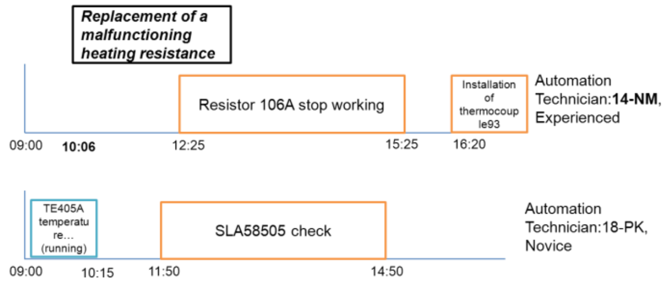

Figure 6: Assigning a technician to an arriving task according to the second scenario.

5 CONCLUSIONS AND FUTURE WORK

This paper presented a feature-rich HR model which allows the optimization of human resources in enterprises. The modelling approach that was followed is described along with the main entities and parameters that are taken into account. Furthermore, a novel multi-criteria task assignment method which attempts to assign an arriving task to the most appropriate employee(s) in enterprises was presented. The task assignment method takes into consideration diverse information such as the remaining workload, task overlapping and estimations provided by CRF probabilistic models trained with historical task assignments in order to rank the candidate employees based on suitability. Initial evaluation showed that effective and even optimal decisions can be made according to the selected assignment policy.

The advantage of the proposed HR model is its ability to encapsulate the entities and information required for allowing the automated decision making and minimizing human intervention when HR management-related actions are needed. However, the estimations produced by the probabilistic models are not available in case a new type of task which has not been seen before has to be assigned. Furthermore, the ranking of employees based on proximity to the task requires localization hardware to be installed. We believe that since advanced sensing solutions are becoming more widespread and IT infrastructure is gaining a key role in enterprises' shop floors, automated real-time monitoring and evaluation of the work, operations and production process towards decision support is feasible. Since such functionality could improve convenience and reduce response times when unexpected events occur, we believe it is worthwhile for an enterprise to invest in such a solution.

As a future work, we intend to extend the proposed method to support task scheduling by extracting as output the scheduled starting time of tasks as well. We also plan to enhance the CRF probabilistic models by adding extra features, and utilize the information about the current location of employees into the HR assignment method.

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