Factors affecting the development of workforce versatility

El-Awady ATTIA*, Virgil DUMBRAVA**
Philippe DUQUENNE*

**Toulouse University, INP/ENSIACET, LGC-UMR-CNRS 5503/PSI/ Industrial engineering department*
4 allée Emile Monso – BP 44362, 31030 Toulouse cedex 4, France
(Tel: +33-534323661; e-mail: {elawady.attia, philippe.duquenne}@ ensiacet.fr).

** *Electric Power Systems Department, Faculty of Power Engineering, University POLITEHNICA of Bucharest,*
313 Splaiul Independentei, Sector 6, Bucuresti 060042, Romania (Tel: +4-0744420184; e-mail: v_dumbrava@yahoo.com)

Abstract: Among all strategies supporting the firms' flexibility and agility, the development of human resources versatility holds a promising place. This article presents an investigation of the factors affecting the development of this flexibility lever, related to the problem of planning and scheduling industrial activities, taking into account two dimensions of flexibility: the modulation of working time, which provides the company with fluctuating work capacities, and the versatility of operators: for all the multi-skilled workers, we adopt a dynamic vision of their competences. Therefore, this model takes into account the evolution of their skills over time, depending on how much they were put in practice in previous periods. The model was solved by using an approach relying on genetic algorithm that used an indirect encoding to build the chromosome genotype, and then a serial scheduling scheme is adopted to build the solution.

Keywords: Human resources flexibility, versatility, working time modulation, project planning and scheduling, workforce allocation, heterogeneous dynamic skills.

1. INTRODUCTION

Firms have been searching for long for developing their ability to face unpredictable situations. Amongst the many ways of developing their reactivity (Démery-Lebrun, 2005), this work deals with the human capital as a source of internal flexibility. Developing it is not costless, therefore we will investigate some factors affecting the cost of developing one of the human resource characteristics that is known as multi-skills, multi-disciplinary, polyvalence, or versatility,…etc.
Many recent academic research works were conducted dealing with this flexibility dimension in different applications and with the importance of implementing cross-training or job-rotation programmes (Corominas et al., 2006; Yang et al., 2007). This importance results from the intention to preserve and develop the firms' core competences (Hitt et al., 1998), furthermore to enhance their ability to face non-predictable changes. This intension appears in recent works within many applications, as production management (Franchini et al., 2001), software production technology (Li and Womer, 2009), software development (Drezet and Billaut, 2008), or energy production (Eitzen et al., 2004). The productivities of operators in planning and scheduling applications have been considered in previous works based on (static/dynamic) nature, or (homogeneous/heterogeneous) characterisations: here, 'static' means that the operators' productivities are constant, whereas in the dynamic case, these productivities may evolve with experience. When a given operator masters different skills (here, skills are competencies including technical and job-related know-how), the term 'homogenous' indicates that the working efficiency level is the same for all of his skills, and the term 'heterogeneous' means that his productivity may differ from one skill to another. About these two parameters, one can refer to the works of Franchini et al. (2001); Drezet and Billaut (2008); Li and Womer (2009) for adopting the static/homogeneous case. And, concerning the static heterogeneous implementation we can find the work of Heimerl and Kolisch (2009); Attia et al. (2012). The dynamic heterogeneous consideration is described in Sayin and Karabati (2007); Hlaoittinun et al. (2010); Attia, et al. (2011a).

The model that we used in the present investigation study is a project scheduling with multi-period workforce allocation. This model was presented in Attia et al. (2011a) and takes into account two dimensions of human resources flexibility: the workforce polyvalence and their flexible working time – known as working time modulation. Within it, the workers' (we call them actors) timetable can fluctuate on daily or weekly bases in due respect to the working time regulation and agreements. In addition it considered a heterogeneous and dynamic nature of the operators' productivities. The starting point is that if firms are willing to develop versatility, they should accept extra costs – the question being: how can we reduce these extra costs and simultaneously develop the competences? This work is intended to study and discuss some of the factors that can help to achieve this result, by using the model as a decision-making tool for human resources management.

This paper is organized as follows: the next section presents the factors that can affect the development of workforce versatility; Section 3 discusses the characterization of the model's different parameters that are used in the investigation. Section 4 shows the approach we adopted to solve the problem, with results and analysis provided in section 5. In the end we present our conclusions and perspectives.

2. FACTORS TO BE INVESTIGATED

In this section we discuss three groups of parameters: the first is related to the human resources themselves, the second is associated to the firm's core competences, and the third is the firms' managerial strategy for developing workers flexibility.

2.1 Parameters associated to human resources

Actors' number is the number of employees involved in the development program: the cost of developing their versatility will be all the higher as they are numerous. As indicated in the work of Attia et al. (2011a), firms should accept to increase their over costs and reduce their profits just for preserving the productivity of multi-functional operators.

Actors' occupation rates: one can link this factor to the total number of available actors. As the number of actors available for a given job increases, the workforce occupation rate reduces: on one hand, the future temporal flexibility is preserved; on the other hand, an erosion of efficiencies may result from a decrease of workers' mean practicing rate.

The actor's number of skills is the number of skills that one actor can master with optimal or acceptable performance. This number sometimes is used to represent the workforce flexibility degree (Kher et al., 1999). We can fear that, as the number of an actor's skills increases, the probability of practice interruption grows, resulting in skills attrition – especially in case of low similarities between these skills. Kher et al. (1999) investigated the number of different skills for which a worker should be trained, and how to train the workers, and how to assign the workers in order to increase the learning and reduce the loss of learning.

The minimum productivity level simply indicates a minimum accepted efficiency level $\theta_{a,k,(min)}$ for an actor *a* in a skill *k*, below which the practice of this skill by this actor is not desirable for economic or quality reasons. In this article we will investigate the effect of this factor in the skills attrition, to show whenever one can use the actor's versatility.

Rates of learning / forgetting: the workforce experience evolves as a function of the actors' practice. These parameters may vary from one worker to another and from one skill to another. Experimental studies (Bailey, 1989; Globerson et al., 1989; Kher et al., 1999) showed that skill attrition depends on the duration of continuous learning without interruption, and on the duration of the interruption period. According to Jaber et al. (2003), forgetting and learning rates are related, and Nembhard and Uzumeri (2000) found from an empirical investigation that the actors who learn faster are likely to forget rapidly.

Some other factors have been listed in the literature: the impact of the *Teamwork* structure as a micro-social system was described by Huang et al. (2010); *Social relations* were investigated by Alexopoulos (2008) who pointed out the importance of personal and professional trust on knowledge transfer; and Dam (2003) studied *Actors' attitudes* (motivation, willingness, …) and concluded that the individual factors have more influence than organizational ones on flexibility development. These factors have not been included in the work described here – but will be its logical continuation.

2.2 Parameters associated to skills

The similarity degree represents the level of similarity between two skills; it relies on the attributes that are common between the two skills (knowledge fields, use of common tools, machines, raw materials, etc.), and can be calculated relying on one of similarity measures such as *Euclidean distance,* for instance. As discussed by Jaber et al. (2003), this factor can affect the skills attrition, (see further, section 5) – in the present paper, it will figure the easiness (or difficulty) to get a given additional skill beside a core-competence.

Here again, some other factors have been reported to have significant effect: the *skill type* (cognitive or motor skill) has been investigated by Dar-El et al. (1995); Globerson et al. (1998); Nembhard and Uzumeri (2000). Moreover, Yelle (1979) discussed the influence of *Actor/machines work contents percentage* on the time required to reach steady-state productivity.

2.3 Firms' policies about flexibility

Training policies express the way the company will use, or not, the actors during their competency acquisition periods (Kher et al., 1999): in our case, it can be represented by the workforce *minimum productivity level,* $\theta_{a,k,(min)}$, as introduced in *2.1*.

We also can mention here, but it is not developed in the paper, the *transfer frequency* and its impact on learning and attrition rates, studied by Khmer et al. (1999), based on the Learning-Forgetting-Learning model of Carlson and Rowe (1976); the *firms' motivation to develop flexibility* points out the firm's appreciation of multi-skilled workforce - translated into how much over costs will be accepted by the management to develop multi-skilled actors.

3. CHARACTERISATION OF THE MODEL

In order to investigate the effect of these parameters we will use a simulation model of project scheduling with synchronized human resources allocation, presented in Attia et al (2011a., 2012). Aiming to reflect real situations, it contains shortage/excess of available resources that can force managers to temporarily abandon some of the allocation strategies in order to achieve a project. The characteristics of the different model dimensions will be briefly discussed in this section:

3.1 Project characterisation

A project is broken down into a set *I* of unique and original tasks. We assume that each task *i* is well defined, as is the required set of skills (nk_i) needed to carry it out (in this view, more than one skill may be required to execute one given task). For each skill $k \in (nk_i)$ associated to a task *i,* we have a standard workload ($\Omega_{i,k}$) expressing the standard working time (in hours for instance) of this skill that is needed to perform it. We assume that the start date is the same for all the workloads related to the same task. We thus determine the task duration as the maximum duration of its associated workloads, i.e. $df_i = Max\ (df_{i,k})$ ($\forall i$, and $\forall k \in nk_i$), where df_i is the finish date. Concerning the tasks durations, for each task *i,* we provide minimal (D_i^{min}), standard (D_i), and maximal (D_i^{max}) durations (in days for instance). The real duration of the task (d_i) must satisfy the relation: $D_i^{min} \leq d_i \leq D_i^{max}$. As discussed earlier, one of the task characteristics is the number of skills (nk_i) required to its achievement, and the workloads ($\Omega_{i,k}$) associated to these skills. Hence, for each skill-related workload there is a real duration $d_{i,k}$ (in days). As a result the tasks execution period can be calculated as: $d_i = \underset{k \in nk_i}{Max}\{d_{i,k}\}$, $\forall i$.

The most important variable to determine the task duration and hence the project schedule is the variable ($d_{i,k}$): this duration is deduced from the equivalent productivity of the teamwork ($EE_{i,k} = \sum \theta_{a,k}$, $\forall a \in teamwork$) allocated to achieve the corresponding workload, beside to their daily working capacity ($\omega_{a,i,k,j}$). Therefore, $d_{i,k} = \Omega_{i,k} / [(\omega_{a,i,k,j} \times EE_{i,k}]$, $\forall k \in nk_i$, and $\Omega_{i,k} \neq 0$. The order of undertaking tasks is governed by their scheduling: the constraint between a predecessor *i* and a successor *c* lays between their start dates (Demeulemeester and Herroelen, 2002), and can integrate a time delay $l_{i,c}$: $dd_i + l_{i,c} \leq dd_c$. Finally, regarding the project duration, we assumed that the project is held to a contractual delivery date *L*, to which is attached a "grace period" β. If the results are delivered to the client with a delay greater than β, some lateness penalties are charged; we also avoid to achieve the project earlier than $(L-\beta)$ in order to avoid storage costs: accordingly, the real project delivery date *(LV)* must be in the interval $[L-\beta , L+\beta]$.

3.2 Characterisation of workforce

We characterized the human resources according to three attributes; their versatility, the dynamic evolutions of their experience, and their flexible working timetable; *Versatility*: each actor can master a set of skills beside his basic one, with a given efficiency for each. This efficiency $\theta_{a,k}$ of the actor *a* in the competence *k* (Duquenne et al., 2005) will be calculated as the ratio ($\theta_{a,k} = \Omega_{i,k} / \omega_{a,i,k}$) of the standard workload (in hours) $\Omega_{i,k}$ required from the competence *k* to complete the activity *i*, to the working time actually needed by the actor *a* to achieve this workload $\omega_{a,i,k}$. If $(\theta_{a,k}=1)$, the actor *a* is considered as an expert in this skill, and he will perform the job within the standard duration. If not, we consider that the actor's efficiency is within the interval:] 0, 1[.

The evolutions of workforce experience: Since Wright (1936), it is known that the effort required from the same actor to achieve a given task decreases each time the task is repeated. Referring to Wright's model, we presented the evolution of the efficiency $\theta_{a,k}$ (Attia et al., 2011b) as a function of three parameters: n_{eq} represents the number of equivalent work repetitions prior the allocation date $(dd_{i,k})$: we express it with the subscript ($n_{eq} \rightarrow dd_{i,k}$). The second factor $\theta_{a,k}(ini)$ is the actor's initial efficiency, measured at the first time he is allocated with the considered skill. The third, the exponential factor *(b)*, is calculated from the actor's rate of learning $(r_{a,k})$, as $b=log\ (r_{a,k})/log(2)$.

$$\theta_{a,k(n \rightarrow ddi,k)} = 1/[1+(1/\theta_{a,k}(ini) - 1)\times(n)^b] \qquad (1)$$

Reciprocally, the lack of practicing a given skill induces attrition of the actors' efficiency, due to a forgetting effect. In equations (2) and (3) (Attia et al., 2011a), we represent the evolutions of actors' efficiencies during the work interruption periods as a function of four parameters, according to Wright (1936) and Jaber and Bonney (1996). The first two parameters are, as previously defined, the initial efficiency $\theta_{a,k}(ini)$, and the exponential parameter (*b*); additionally, *f* represents the exponential parameter of the forgetting curve, and ξ is the ratio between two periods $(\xi = Tb / Ta)$: *Ta* is an uninterrupted period of practicing the specified skill, and *Tb* is the interruption period after which the actor's efficiency has decreased down to its initial value. In eq. (2), λ is the number of work repetitions that would have been performed if the interruption didn't occur.

$$\theta f_{a,k} = 1/[1+(1/\theta_{a,k}(ini) - 1)\times(n_{eq})^{b-f}\times(n_{eq} +\lambda)^f] \qquad (2)$$

$$f = -b \times(b+1) \times log\ (n_{eq})/log\ (\xi+1) \qquad (3)$$

The *flexible working timetable*: according to the strategy of annual working time, each worker has a fixed amount of working hours per year. This amount can be spread unevenly over the timetable horizon. Therefore each actor's timetable may present fluctuations in daily and weekly bases, but it should respect the law constraints on maximum periods of work (normal and extra hours) per day, per week, or even through a period of twelve consecutive weeks, in addition to the annual threshold; for more details on the modelling of these constraints, see the authors work in Attia et al. (2012).

3.3 Cost – based objectives

By the end of the project, the company seeks to optimize five objectives: four cost terms $(f_1,…, f_4)$ to be minimized, and one virtual profit function (f_5) to be maximized. The term (f_1) represents the cost of actors' standard working hours; (f_2) is the cost due to overtime hours, added to (f_1) to represent the total project labour cost. The term (f_3) represents a virtual cost associated to the loss of actors' work flexibility at the end of the simulation. The term *(f_4)* is a penalty cost associated to the completion of the project outside the tolerance interval. Finally, the virtual profit/cost *(f_5)* is related to the bulk evolution of actors' efficiencies in mastering the skills considered. For a more detailed description of these objectives, one can refer to the work of Attia et al. (2011a, 2012). Finally we aim to minimise the function *F*:

$$F = f_1 + f_2 + f_3 + f_4 - f_5 \quad (4)$$

4. PROBLEM SOLVING APPROACH

The resulting model is nonlinear, with mixing binary, integer, and real variables. Therefore, solving it with an exact method is almost impossible. So, we propose to solve this problem with a priority-coding genetic algorithm (GA). Each of the chromosomes will carry priorities for scheduling tasks, priorities for allocating actors, and the working time policies that will be applied. After producing generations of individuals one after the others, a schedule-generating process is started to build the whole project schedule, using a specific allocation approach. That assigns human resources to tasks while respecting both the tasks scheduling constraints and the workforce-related constraints. The use of priority-encoding chromosomes brings two benefits: first it produces shorter chromosomes in comparison to a direct encoding of solutions. For example a problem of (30 tasks, 83 actors, and 4 skills) leads to chromosomes having 3,879 genes, whereas with indirect encoding it drops down to 118. The second reason is the presence of "epistasis" (Gibbs et al., 2006): some of the chromosome's genes are interrelated; in a random process, it increases for each generation the proportion of the chromosomes that represent unfeasible solutions. This approach was validated by investigating manually the results provided for some instances of different sizes (30, 60, 90 and 120 tasks), and different numbers of actors: the algorithm parameters were tuned and then fixed as shown in Table 1.

Table 1. Parameters used in simulations

Population size (PI)	= 50 individuals
Crossover probability	= 0.7
Mutation probability	= 0.01
Regeneration Probability	= 0.1
Max. unchanged generations	= 100 generations
Tolerance period *(β)*	= 20 % ×*L*

5. RESULTS AND DISCUSSIONS

To investigate the effect of the parameters listed above on skills' acquisition and attrition, we designed an experiment based on different instances of project scheduling. Since there is no available benchmark problems for this model (presented in section 3), we have modified some of the benchmark instances available in the library (PSPLib, 1996) with different sizes (30, 60, and 90 tasks), with numbers of actors varying from 56 to 162. We investigated the effects of the following parameters: - The similarity degree (SD) between actor's skills, - The minimum required efficiency level, -The percentage of the actors attending the development program, - The total number of actors, or their average occupation rate, - The number of skills under development per each actor. In order to avoid the stochastic nature of genetic algorithms, each point in the following figures is an average value of the results of 10 simulations performed for the same instance with the same parameters combination, resulting in a total of 720 simulation runs.

- *The effect of the similarity degree (SD)*: one can see the significant effect of this parameter on (fig. 1): the competences attrition [expressed by the fictive value (f_5) in monetary units (UM)] decreases as the similarity between skills increases.

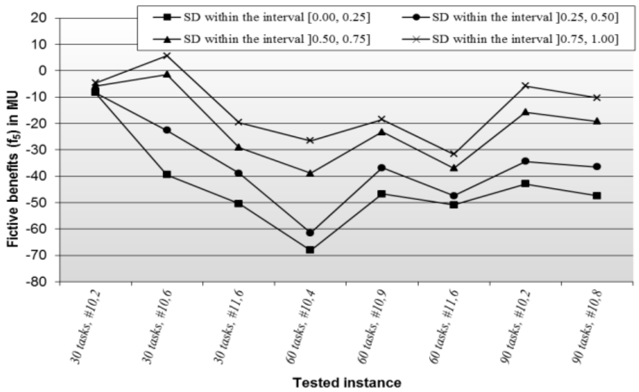

Fig. 1. The effect of SD on the actors' skills attrition.

This effect can be reduced by tuning other parameters such as the minimum efficiency level, as shown by instance (30 tasks, #10.2) for which $\theta_{a,k}(min) = 0.7$ whereas for the other cases $\theta_{a,k}(min) = 0.5$. Thus we are motivated to study it more in details.

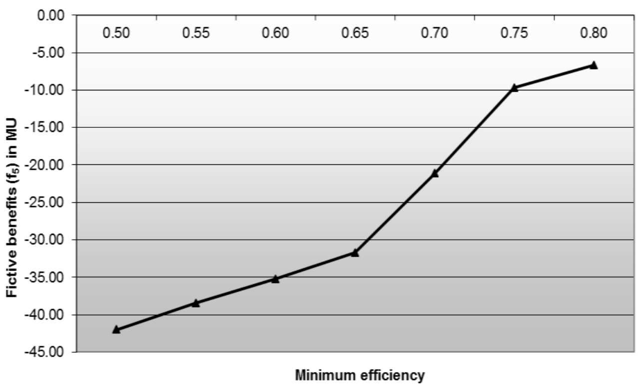

Fig. 2. The effect of $\theta_k(min)$ on the actors' skills attrition.

- *The effect of the minimum productivity level of workers $\theta_{a,k}(min)$:* this parameter represents the minimum level of actors' efficiency allowing the use of a secondary skill. We investigated this parameter on a project instance (30 tasks, #10.6) with (*SD= zero*), as indicated by (fig. 2). One can notice that skills attrition decreases as $\theta_{a,k}(min)$ rises. We link this effect to two reasons; the experience level: skills attrition slows down when the worker becomes more and more expert.

The second reason is the number of workers; as the required level $\theta_{a,k}(min)$ is raised, the number of actors available for a given job is reduced, decreasing the risk of job interruption for each of them.

- *The percentage of multi-skilled actors who attend the development program*: in order to investigate this parameter, we take only one project (30 tasks, #10.6), and modify the actors' descriptions to give the following instances: The first instance is a reference in which no actor is polyvalent, i.e. each actor has only one skill with nominal efficiency. Other four instances have been modified so that each one represents a specified percentage (10%, 26%, 42%, and 53%) of actors following the versatility development program, with only one additional skill in all the cases. As shown by (fig. 3), the percentage of actors concerned by the program increases the risk of skills attrition, for the same ranges of actors occupation rates, - but this effect can be reduced by increasing the similarity degree between skills.

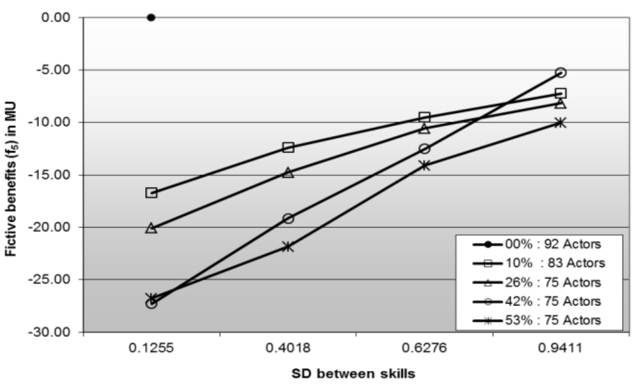

Fig. 3. The effect of the number of multi-skilled actors.

- *The actors' average occupation rate*: to investigate this parameter we reduced the number of the actors who have only one skill in order to increase the occupation rates of the polyvalent ones.

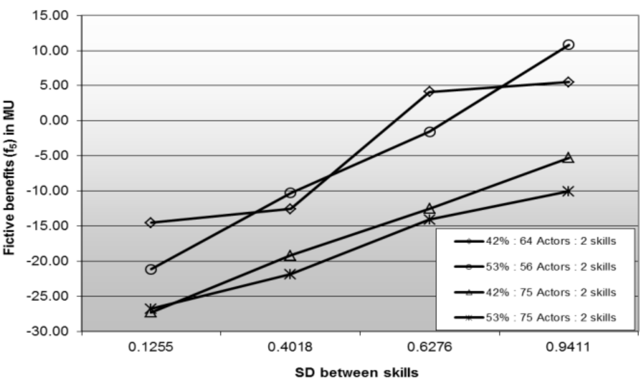

Fig. 4. The effect of actors' occupation rates.

As shown by (fig. 4), considering that the number of multi-skilled actors isn't changed, when the actors' average occupation rates grow the skills attrition effect is reduced, moreover their skills can be developed especially for high similarity degrees between skills. One of our conclusions here is: "if an operator has to attend a multi-skill development program, the strategy of preserving his future temporal flexibility can be temporary abandoned, and it is better to spread regularly a sufficient part of his annual hours on the skill's acquisition period, which can enhance the skill's development and reduce the attrition effect".

The number of skills under development for each actor: We used the same project (30 tasks, #10.6), but instead of only one secondary skill per actor, we have generated another additional skill for all operators who follow the program. As shown by (fig. 5), the skills' attrition is all the more important as the number of skills per actor increases.

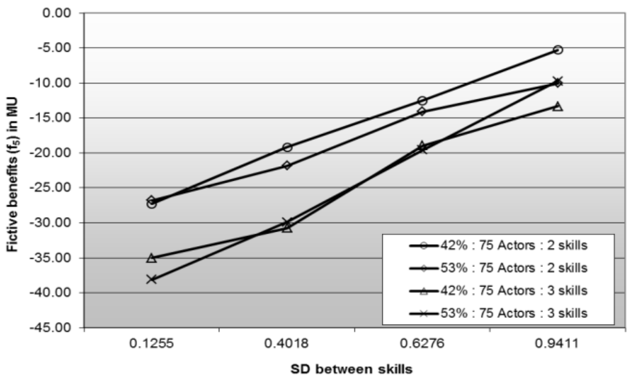

Fig. 5. The effect of the number of skills per actor.

Finally, In order to test the statistical correlation between the different listed parameters and the fictive benefits of skills' development, we used the "Pearson product moment correlation coefficient", known as "Pearson's correlation". Results show that the fictive benefits *(f_5)* can be linearly related to the similarity degree between skills (with Pearson correlation factor and P-value equal to 0.590 and 0.000, respectively), to the number of skills per actor (-0.547/0.001), to the workforce average productivity (0.362/0.038), and to the future work flexibility preservation (which is inversely related to the occupation rates) with (-0.452/0.008). Thus there is sufficient evidence with significant values smaller than 0.05 that the correlations aren't null. In addition it reveals that the fictive benefits are partially correlated to the number of multi-skilled actors (-0.521/0.002) and to the total number of actors (-0.531/0.001) after controlling the effect of the other variables.

6. CONCLUSIONS

In this work, we discussed and investigated some of the parameters that affect the development of the multi-functional as well as temporal flexibility of the workforce in a problem of allocating human resources on industrial activities. This investigation points out the possibility of reducing the effects of skills depreciation, and thus the cost associated to learning-forgetting-relearning phenomena. It also illustrates how an overview of coming activities may turn to highlight the skills that should be strengthened in the future, or the ones that may disappear – and how the operators should be shifted to other missions. Thus, it can be used as a decision-making tool for human resources managers. Amongst our perspectives, we will integrate the social aspects, and teamwork composition, and study their impact on the development of the workforce performance, especially in the case of industrial-scale problems.

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