

# PROPOSITION OF A MODEL FOR MULTI-PERIOD WORKFORCE ASSIGNMENT PROBLEM CONSIDERING VERSATILITY

<sup>1</sup>ABDELHAMID ZAKI, <sup>1</sup>MOHAMMED BENBRAHIM, <sup>1</sup>BAHIA BENCHEKROUN, <sup>2</sup>GHAASSANE AYAD

<sup>1</sup>EMI-Rabat, EMOAD/SCM, BP 765, Agdal, Rabat, Morocco

<sup>2</sup>EMI-Rabat, EMISYS, BP 765, Agdal, Rabat, Morocco

E-mail: zaki.hamid@yahoo.fr, benbrahim@emi.ac.ma, bahia@emi.ac.ma, ghassane.ayad@gmail.com

## ABSTRACT

Workforce assignment becomes more complex when operators have multiple competencies and the operators' efficiency changes according to the activities they are assigned to. In this context, only little work has considered the learning curve effect. In this paper, we will discuss a multi-period assignment problem, considering the versatility of the operators, which induces a dynamic view of their competencies and the need to predict changes in individual performance as a result of successive assignments. We are in a context where the expected durations and the awaited quality execution of activities are no longer deterministic, but results from the performance of the operators selected for their execution. In this article, we will present a mathematical model of this problem and a genetic algorithm approach to solve the workforce multi-period allocation problem.

**Key words:** *Competence, Multi-Skilled Workforce, Individual Competence Level, Versatility, Multi-Period Assignment Problem, Performance.*

## 1. INTRODUCTION

In a manufacturing enterprise, the production is controlled by a management system which must respect a set of constraints in order to achieve defined objectives. Transformation takes place through a succession of operations that uses the resources (material, human and information) belonging to the production system and modifies the raw materials in order to create the finished products with added value. Recently, many research works were conducted dealing with the study of workforce competency in different applications, and the importance of developing multi-skilled workforce to preserve the companies' core competences. [5] introduced a methodology for workforce assignment based on their multi-competency with task execution times influenced by the individual's efficiencies. However, In modeling of operators' efficiencies, the tasks are often approached with predetermined durations. In the service centers, [16] classified the actors into groups (senior, standard and junior), each one has a given productivity factor with

respect to a standard one. [11] proposed a formulation to solve the problem of multi-period allocation in the area of structure design teams with better management of individual skills. The authors are interested in determining allocation decisions allowing both cost reduction and human resources competencies control.

There are many forms of demonstrating the workforce efficiencies and from which we can calculate the tasks' durations. Therefore, [1], [4] and [6] presented their problems of scheduling multi-skilled actors while complying with legislation constraints. They proposed a method to balance the fluctuation in workstation loads with respect to the available workforce, by using flexibility levers such as multi-skilled workforce and working time modulation.

We can find other applications of the multi-skilled individuals' efficiencies in: information technologies' projects [10], the projects portfolio selection [9], the project scheduling problem with the flexibility of

multi-skilled workforce [2]. In this context, we will propose a mathematical model that will demonstrate an integrated method that achieves a compromise between the cost of realization of the production program and the evolution of individual competences. Starting from the static problem, with consideration of individual competencies and arriving at a dynamic problem (considering the evolution of the actors' skills, which consequently increases the complexity of the model), we have thus turned to the use of a meta-heuristic method to solve this problem. This paper is structured as follows:

- Section 2: discusses the context of this study;
- Section 3: describes the modeling of individual performance.
- Section 4: details the modeling of the dynamic evolution of actors' performance. -Section 5: discusses the modeling approach of the assignment problem.
- Section 6: describes the resolution method.
- Section 7: Illustrative example
- Section 8: conclusion.

## 2. THE RESEARCH CONTEXT AND PROBLEM DESCRIPTION

This research paper deals with the study of the scheduling problem with parallel resources considering competences constraint (Figure 2.1). We are interested in the case of production by program. Each activity can be divided into fractions (splitting) which can be executed on several machines. The splitting allows several fractions of the same activity to be executed simultaneously on different workstations, whereas in the case of preemption a fraction of one activity can only begin if no other part of this activity is in progress on another workstation. In this model, we assume that operators are multi-skilled with varied performance and each individual can be characterized by his ability to perform one or more activities with a given performance.

As mentioned previously, the main objective of this study is to assign a set of activities to a set of production operators taking into account their competencies. The assignment problem has been classified into four categories according to two criteria proposed by [12]: the first criterion is the assignment period and it distinguishes two types: mono-period and multi-period. The second criterion deals with the modeling of competencies which can be classified into two categories: static modeling for which the competencies of the actors remain unchanged over time and dynamic modeling

which incorporates competence improvement or depreciation over time. Our modeling approach here is based on a multi-period assignment model which takes into consideration the dynamic evolution of individual competencies. A general assignment problem does not allow highlighting the competence and workload constraints. For this reason, we have characterized each individual by an individual coefficient (IUC) and proposed a mathematical model that allows modeling the dynamic evolution of individual competencies. We have adopted the following logic to model and solve the problem of programming activities that simultaneously consider the three constraints: workforce versatility, equitable distribution of workload and dynamic evolution of competencies. The principal of the resolution method is illustrated as following (Figure 2.2). In this work, we are interested in minimizing the assignment cost while allowing improving individual competencies.

## 3. MODELING OF OPERATORS' EFFICIENCIES

Each operator in the manufacturing industry masters one or more activities with consideration to the operators' efficiencies in different competences. The workforce can be characterized relying on three dimensions: primarily, the "work performance" secondly, the "execution quality" and finally, the "consumption ratio". In this work, we adopted the actors' characterizations discussed by [18]. Therefore, we express an actor's ability to achieve a given activity via three indicators:

$$WP_{ijp} = WP(Q_{ijp}) = \frac{Ts(Q_{ijp})}{Tr(Q_{ijp})} \quad (1)$$

$$EQ_{ijp} = EQ(Q_{ijp}) = \frac{Qg_{ijp}}{Q_{ijp}} \quad (2)$$

$$CR_{ijp} = CR(Q_{ijp}) = \left[ \prod_{k=1}^{k=m_i} CR_{kjp} \right]^{1/m_i} \quad (3)$$

$$= Q_{ijp} \cdot \left[ \prod_{k=1}^{k=m_i} \frac{n_{ik}}{Q_{ijpk}} \right]^{1/m_i}$$

With,

$Q_{ijp}$  : The amount of activity (i) assigned to be done by the operator (j) at the period (p), it corresponds to the planned quantity (Qp);

$Q_{gijp}$  : Compliant production of activity (i) produced by operator (j) at period (p);

$T_s$  : standard time required to execute  $Q_{ijp}$  ;

$T_r$  : real time spent in executing  $Q_{ijp}$  ;

$m_i$  : Number of components required to produce one unit of the activity (i);

$k$  : index of component;

$n_{ik}$  : Number of the component (k) required to produce one unit of the activity (i);

$Q_{c_{ijpk}}$  : The amount of component (k) consumed by the operator (j) at the period (p) to produce the activity (i).

Where,  $WP_{ijp}$  represents the “work performance” of the operator (j) demonstrated at the period (p) when performing the activity (i);

$EQ_{ijp}$  is the “execution quality” of the operator (j) demonstrated at the period (p) when performing the activity (i)

$CR_{ijp}$  is defined as the ratio between the total production carried out by the individual (i) and the quantity of raw material used by the some individual to obtain this total production.

In the next section, we will formulate the extra cost resulting from the assignment of a given activity (i) to a given operator (j) whose initial performance is not optimal. The demonstration is presented in four steps: the first step concerns the extra cost due to additional time related to the working speed; the second step calculate the extra cost due to non-compliant products, the third step calculate the extra cost due to the loss of components which are improperly handled and the fourth step presents a combination of the three extra costs.

### 3.1. Calculation of the extra cost due to the additional time

The extra time ( $T_a$ ) to produce the quantity demanded ( $Q_d \equiv Q_g$ ) is defined as:

$$T_a(Q_d) = T_r(Q_d) - T_s(Q_d) = (1 - WP) \cdot T_r(Q_d) \quad (4)$$

Let,

$$T_s(Q_d) = T_s \cdot Q_p = T_s \cdot \frac{Q_d}{EQ} \quad (5)$$

Replacing (5) in (1), we get:

$$T_r(Q_d) = \frac{T_s}{WP * EQ} * Q_d \quad (6)$$

Substituting (6) in (4), the extra time due to the additional time is:

$$T_a(Q_d) = \frac{1 - WP}{WP * EQ} \cdot T_s \cdot Q_d \quad (7)$$

Assume that the average hourly rate (AHR) corresponds to the overall charges to be covered divided by the number of invoiced hours. The extra cost ( $Cat$ ) due to the additional time ( $T_a$ ) to produce ( $Q_d$ ) is equal to:

$$Cat(Q_d) = T_a(Q_d) * AHR = \frac{1 - WP}{WP * EQ} \cdot T_s \cdot Q_d \cdot AHR \quad (8)$$

### 3.2. Calculation of the extra cost due to poor product:

If ( $EQ < 1$ ), so how much it is the extra cost due to the “non-compliant products”.

Let,

$$\text{non-compliant products} = (1 - EQ) \cdot Q_p = (1 - EQ) \cdot \frac{Q_d}{EQ} \quad (9)$$

Assume that ( $Cr$ ) corresponds to the production cost and ( $Cnq$ ) is the extra cost due to those “non-compliant products” is equal to:

$$Cnq(Q_d) = \frac{1 - EQ}{EQ} \cdot Q_d \cdot Cr \quad (10)$$

### 3.3. Calculation of the extra cost due to the loss of raw material:

If ( $CR < 1$ ), then there is a damaged components due to improper use. Consequently, how much it is the extra cost ( $C_d$ ) due to those “damaged components”? Assume that ( $Cmp_k$ ) corresponds to the purchase cost of components (k), then ( $C_d$ ) is:

$$C_d = \sum_{k=1}^m (Q_{c_k} - Q_{p_k}) \cdot Cmp_k$$

Thus,

$$C_d = \sum_{k=1}^m \left( \frac{1 - CR_k}{CR_k} \right) \cdot Q_{p_k} \cdot Cmp_k$$

$$C_d = \sum_{k=1}^m \left( \frac{1 - CR_k}{CR_k} \right) \cdot n_k \cdot Q_p \cdot Cmp_k$$

$$C_d = \frac{Qd}{EQ} \cdot \sum_{k=1}^m \left( \frac{1 - CR_k}{CR_k} \right) \cdot n_k \cdot Cmp_k$$

Therefore,

$$C_d = \frac{Qd}{EQ} \cdot \left[ \sum_{k=1}^m \left( \frac{n_k}{CR_k} \cdot Cmp_k \right) - \sum_{k=1}^m (n_k \cdot Cmp_k) \right] \quad (11)$$

Assume that ( $Cmp_{1\ unit}$ ) corresponds to the raw material cost needed to produce one unit, with: ( $Cmp_{1\ unit} = \sum_{k=1}^{k=m} n_k \cdot Cmp_k$ ). So, we get:

$$C_d = \frac{Qd}{EQ} \cdot \left[ \sum_{k=1}^m \left( \frac{n_k}{CR_k} \cdot Cmp_k \right) - Cmp_{1\ unit} \right] \quad (12)$$

We pose the following hypothesis:  $CR_k = cte$ ,  $\forall k$ . So,  $CR_i = \left[ \prod_{k=1}^{k=m_i} CR_k \right]^{1/m_i} = CR_k$

Therefore:

$$C_d = \frac{Qd}{EQ} \cdot \left[ \sum_{k=1}^m \left( \frac{n_k}{CR_i} \cdot Cmp_k \right) - Cmp_{1\ unit} \right]$$

Thus:

$$C_d = \frac{Qd}{EQ} \cdot \left[ \frac{Cmp_{1\ unit}}{CR_i} - Cmp_{1\ unit} \right]$$

Finally we get:

$$C_d = \frac{1 - CR}{EQ \cdot CR} \cdot Qd \cdot Cmp_{1\ unit} \quad (13)$$

### 3.4. Calculation of the total extra cost:

Considering the expressions of  $Cat$ ,  $Cnq$  and  $Cd$  are given previously in (8), (10) and (13), the total extra cost ( $Ct$ ) due to the individual underperformance is equal to:

$$Ct(Qd) = Cat(Qd) + Cnq(Qd) + Cd(Qd) \quad (14)$$

Then,

$$Ct(Qd) = \left( \frac{1 - WP}{WP \cdot EQ} \cdot Ts \cdot AHR + \frac{1 - EQ}{EQ} \cdot Cr + \frac{1 - CR}{EQ \cdot CR} \cdot Cmp_{1\ unit} \right) \cdot Qd \quad (15)$$

Divide this expression by ( $Qd$ ) gives the extra cost per unit produced ( $Csu$ ):

$$Csu = \frac{1 - WP}{WP \cdot EQ} \cdot Ts \cdot AHR + \frac{1 - EQ}{EQ} \cdot Cr + \frac{1 - CR}{EQ \cdot CR} \cdot Cmp_{1\ unit} \quad (16)$$

We considered that the production cost ( $Cr$ ) is equal to the sum of the raw material cost ( $Cmp_{1\ unit} = \sum_{k=1}^{k=m} n_k \cdot Cmp_k$ ) and the manufacturing cost ( $AHR \cdot Ts$ ), so:

$$Cr = Cmp_{1\ unit} + AHR \cdot Ts \quad (17)$$

We set:

$$\alpha = \frac{Cmp_{1\ unit}}{Cr} \quad (18)$$

Replacing the above expressions given in (17) and (18) in (16), we get:

$$Csu = \left( \frac{1 - WP}{WP \cdot EQ} \cdot (1 - \alpha) + \frac{1 - EQ}{EQ} + \frac{1 - CR}{EQ \cdot CR} \cdot \alpha \right) \cdot Cr \quad (19)$$

We can deduce that the extra cost is directly related to the individual performance which is the combination of the three indicators ( $WP$ ,  $EQ$  and  $CR$ ). We choose to call this aggregate indicator “the individual underperformance coefficient ( $IUC$ )” denoted by:

$$IUC_{ij} = \frac{1 - WP_{ij}}{WP_{ij} \cdot EQ_{ij}} \cdot (1 - \alpha_i) + \frac{1 - EQ_{ij}}{EQ_{ij}} + \frac{1 - CR_{ij}}{EQ_{ij} \cdot CR_{ij}} \cdot \alpha \quad (20)$$

Consequently, the individual ( $j$ ) is considered as an expert in the activity ( $i$ ) when ( $IUC_{ij} = 0$ ) and this case is possible when  $WP_{ij} = 1$ ,  $EQ_{ij} = 1$  and  $CR_{ij} = 1$ . This formulation will be introduced in the allocation modeling.

## 4. MODELING THE EVOLUTION OF INDIVIDUAL PERFORMANCE

The learning by practice or loss of competencies by forgetting effect reflects the

dynamic vision of the workers efficiency. In workforce assignment model, the learning curve effect on productivity can be used to differentiate the performance of operators in the same activity. Individuals with a higher competency level can carry out certain tasks better or faster than individuals with a lower competency level. In this section, we will propose a modeling of these learning and forgetting phenomena. Each operator can perform a given activity more efficiently if they carry out the same activity as long as possible. The amount of time required to perform this activity will decrease every time the activity is repeated.

This phenomenon was first described by [17] who reported it as one of the factors that affects the cost of airplanes. In recent years, the learning curves are incorporated into the workforce scheduling model. [8] compared performance of existing well-known learning curves using a large set of empirical data and showed how to select appropriate learning curves based on task characteristics. [14] proposed a precedence graph approach based on learning from multiple sources of information available to generate new feasible assembly line balances in mass production of complex product. Others as [15] developed a workforce scheduling model for assigning tasks to multi-skilled workforce by considering learning of knowledge and requirements of project quality. The proposed model is improved by taking account of the upper bound of employees' experiences accumulation, and the stable performance of mature employees. Regarding the modeling of learning phenomenon introduced in the literature, the most common representation of experience curves is the exponential function of [17]:  $Y = C_1 X^b$ . Where: Y is the production cost at unit X;  $C_1$  is the first unit production cost and b is the learning curve exponent. Based on the exponential representation, we will present a model that analyzes the extra cost expressed in terms of the individual underperformance coefficient (IUC) of an individual whose efficiency is not optimal. Equation (21) describes the evolution of this additional cost with the number of repetitions of work (X):

$$Csu_{ij}(X) = Csu_{ij}(1) \cdot X^b \quad (21)$$

In this equation, the extra cost is represented by the  $Csu_{ij}(X)$  value for an operator whose underperformance is IUC<sub>ij</sub>, and who is allocated for an activity (i) defined by a standard time (Ts); for this activity,  $Csu_{ij}(1)$  is the extra cost found at the first assignment. The parameter "b" can be expressed as:  $b = \text{Log}(ri, j) / \text{Log}(2)$  where (ri, j)

expresses the learning rate of the individual (j) in the activity (i). The value of  $Csu_{ij}(X)$  is the extra cost found after X repetition of the same work by the same operator without interruption. We can then derive the evolution of the efficiency of an actor from the previous efficiency expressed through the value of (IUC), as shown in equation (23). First of all, let us present the following demonstration:

$$\text{Let, } Csu(X) = Csu(1) \cdot X^b$$

$$\text{With, Cr. IUC}(X_0) = \text{Cr. IUC}_{\text{initial}} \cdot X_0^b$$

$$\text{So, IUC}(X_0) = \text{IUC}_{\text{initial}} \cdot X_0^b$$

$$\text{Let, } X_0^b = \frac{\text{IUC}(X_0)}{\text{IUC}_{\text{initial}}} \text{ with, } \log X_0^b = \log \frac{\text{IUC}(X_0)}{\text{IUC}_{\text{initial}}}$$

$$\text{So, } b \cdot \log X_0 = \log \text{IUC}(X_0) - \log \text{IUC}_{\text{initial}}$$

$$\text{Then, } \log X_0 = \frac{\log \text{IUC}(X_0) - \log \text{IUC}_{\text{initial}}}{b}$$

Therefore,

$$X_0 = 10^{\left[ \frac{\log \text{IUC}(X_0) - \log \text{IUC}_{\text{initial}}}{b} \right]} \quad (22)$$

At the repetition  $X = X_0 + 1$  :

$$\text{IUC}(X_0 + 1) = \text{IUC}_{\text{initial}} \cdot (X_0 + 1)^b \quad (23)$$

Replacing (22) in (23), we obtain:

$$\begin{aligned} & \text{IUC}(X_0 + 1) \\ &= \text{IUC}_{\text{initial}} \cdot \left( 10^{\left[ \frac{\log \text{IUC}(X_0) - \log \text{IUC}_{\text{initial}}}{b} \right]} + 1 \right)^b \end{aligned}$$

Therefore, we can model the increase of efficiency based on the number of allocation periods, and depending on the previous operator's efficiency ( $\text{IUC}(p-1)$ ). So, in function of the period allocation (p), the formula becomes:

$$\begin{aligned} & \text{IUC}(p)^{\text{ass}} \\ &= \text{IUC}_{\text{initial}} \cdot \left( 10^{\left[ \frac{\log \text{IUC}(p-1) - \log \text{IUC}_{\text{initial}}}{b} \right]} + 1 \right)^b \end{aligned} \quad (24)$$

Reciprocal to the development of the individuals' efficiency, we can conclude that the degradation of this experience is due to the lack of practice of a specified activity induced by work interruptions. This phenomenon is known as "forgetting effect". The amount of experience deterioration depends on the amount of experience gained prior to the interruption, the rate of forgetting and the length of the interruption period [13]. As mentioned above, the individual efficiency is degraded when the individual have to work on other activity. According to [3], the forgetting curve relation



is:  $\hat{T}_x = \hat{T}_1 x^f$ . Where  $\hat{T}_x$  is the time for the  $x^{th}$  unit of lost experience of the forgetting curve,  $x$  is the amount of output that would have been accumulated if interruption did not occur,  $\hat{T}_1$  is the equivalent time for the first unit of the forgetting curve, and  $f$  is the forgetting slope.

In our method, an interruption occurs when an individual is not assigned to the same activity in the next period. According to this exponentially-decreasing representation used by [3] and similar to the previous demonstration, we can model the depreciation of efficiency based on the number of interruption periods and depending on the previous operator's efficiency ( $IUC(p-1)$ ), as shown in equation (25):

$$IUC(p)^{inter} = IUC_{initial} \cdot \left( 10^{\left[ \frac{\log IUC(p-1) - \log IUC_{initial}}{f} \right]} + 1 \right)^f \quad (25)$$

Where  $IUC(p)^{inter}$  is the individual's underperformance level after a period of interruption ( $Y$ ), and ( $f$ ) is the slope of the forgetting curve which can be calculated as follows:  $f = -\text{Log}(k_i, j) / \text{log}(2)$ . Where ( $k_i, j$ ) indicates the forgetting rate of the individual ( $j$ ) in the activity ( $i$ ). This rate may vary from one individual to another and from a competence to another. The learning-forgetting relationship is illustrated in (Figure 3.1).

In this part, we summarized everything that has been discussed previously. Let:

$Q_{ijp}$ : The amount of activity ( $i$ ) assigned to be done by the operator ( $j$ ) at the period ( $p$ ) with  $Q_{ijp} \in [Q_{ls,i}, Qd_{ip}]$  else  $Q_{ijp} = 0$ ;

$Q_{ls,i}$ : Minimum lot size;

$Qd_{ip}$ : The quantity demanded of the activity ( $i$ ) at the period ( $p$ );

$IUC_{ijp} = IUC(Q_{ijp})$ : The individual underperformance coefficient of the operator ( $j$ ) demonstrated at the period ( $p$ ) when performing the activity ( $i$ ).

$IUC_{ijp}^{(ass)}$ : The initial underperformance coefficient at the start of the assignment phase after the interruption phase (Figure 3.1). This expression remains constant during the assignment phase. The index  $p_{(inter)}$  informs about the last interruption

period (the period when the assignment has occurred).

$IUC_{ijp}^{(inter)}$ : The initial underperformance coefficient at the start of the interruption phase after the assignment phase (Figure 3.1). This expression remains constant during the interruption phase. The index  $p_{(ass)}$  informs about the last assignment period (the period when the interruption has occurred).

Therefore,

if  $p = 0$

$$IUC_{ij0} = \frac{1 - WP_{ij0}}{WP_{ij0} \cdot EQ_{ij0}} * (1 - \alpha_i) + \frac{1 - EQ_{ij0}}{EQ_{ij0}} + \frac{1 - CR_{ij0}}{EQ_{ij0} \cdot CR_{ij0}} \cdot \alpha_i$$

if  $p \geq 1$

$$IUC_{ijp} = IUC_{ijp}^{(ass)} \cdot \left( 10^{\left[ \frac{\log IUP_{ij(p-1)} - \log IUC_{ijp}^{(inter)}}{b} \right]} + 1 \right)^b ; \text{ if } Q_{ijp} \geq Q_{ls,i}$$

$$IUC_{ijp} = IUC_{ijp}^{(inter)} \cdot \left( 10^{\left[ \frac{\log IUP_{ij(p-1)} - \log IUC_{ijp}^{(ass)}}{f} \right]} + 1 \right)^f ; \text{ else}$$

In summary, the IUC value allows us firstly to quantify the individual performance and secondly to calculate the cost incurred when the individual is assigned. We have used the principal of the learning curve proposed by [17] in order to model the dynamic evolution of individual competencies and we have expressed the evolution of IUC value regarding the previous performance which will be affected by the decision assignment. The use of this model will allow us to control the assignment solution which is in not in favor of versatility.

## 5. THE MODELING APPROACH

In this model, we will assume that each worker can be characterized by his/her capacity to perform one or more activities. On the other hand, worker's effectiveness is specific to each individual and is measured for each activity. As we have seen, the level of competence of each operator determines his/her coefficient of underperformance (IUC) to realize a defined load. The duration, quality of execution and consumption ratio for each activity is therefore not predetermined but is a result from previous periods of assignments and /or interruptions.

Each actor has his/her own individual coefficient (IUC), which is variable during the assignment process. We recall that our modeling approach deals with a multi-period assignment problem taking into account the dynamic evolution of individual competencies. We are simultaneously pursuing three different objectives. First is to ensure a balanced distribution of workloads. Second objective is to respect the time constraints governing working time. And third and final objective is to find a compromise between the assignment cost and the evolution of individual competencies.

The problem can be presented as follows: A production planning consists of a set of P periods, a set of N activities and a set of M workers; we consider the actors are multi-skilled. The ability of each individual (j) to practice a given activity (i) is expressed through his efficiency in term of his ( $IUC_{ij}$ ).

In addition to the individuals' versatility objective, we consider that the company adopts a strategy of the uniform repartition of the workload : the workloads of its employees should be the same for each period. Thus, we will focus at three different targets: minimize the assignment cost; ensure a balance between the workloads required and the individuals' availabilities and maximize the individuals' efficiencies. As a result, the problem consisting in minimizing a multi-objectives function which is a subject to a set of allocation constraints. In order to develop individual experience with lower cost, the amount of work of each activity at each period is considered as a decision variable.

### 5.1. Problem parameters

We have a problem defined by the following parameters:

$Q_{ijp}$  : Decision variable related to the amount of work (i) assigned to be done by the operator (j) at the period (p),  $Q_{ijp} \in [Q_{ls,i}, Q_{d_{ip}}]$  or  $Q_{ijp} = 0$ ;

$Q_{d_{ip}}$  : The quantity demanded of the activity (i) at the period (p);

$IUC_{ijp}$  : Operators' underperformance when the operator (j) performs the task (i) in period (p);

$Cr_i$  : Production cost of the activity (i);

$C_{HD}$  : Virtual penalty cost related to any workload that would finish outside the weekly working hours;

$HD_{jp}$  : Available working hours per period (p) of the individual (j), it represents the maximum working hours of any individual;

$Cp_i$  : Theoretical production rate of the activity (i);

$Q_{ls,i}$  : Minimum lot size;

$CT_p^{tot\_eff}$  : The effective workload at period (p);

$CT_p^{moy\_eff}$  : Average effective workload at period (p);

$CT_{jp}^{ind\_eff}$  : Effective workload of the individual (j) at period (p);

$NB_{op}$  : Number of workers.

### 5.2. Objective function

We are interested in minimizing the cost of execution of each activity by targeting a better correspondence between the skill levels acquired by each individual and those required by each activity. The objective function is composed of three terms, as shown in equation (30).

$$F(Q_{ijp}) = F_1(Q_{ijp}) + F_2(Q_{ijp}) + F_3(Q_{ijp}) \quad (26)$$

The first term ( $F_1$ ) represents the additional cost due to underperformance manifested by operators, with standard production cost ( $Cr$ ) as shown in equation (27) .

The second term ( $F_2$ ) represents the objective associated to individuals' overcharging as illustrated in equations (28) : it is a function of the difference between individuals' workload and

the average workload per period, and it favors the solutions with minimum gap.

The term ( $F_3$ ) represents the fictive gain of individuals' efficiencies developments. It is calculated as shown in equation (29) by comparing the individuals' efficiencies after the assignment horizon with the targeted performance level.

$$F_1(Q_{ijp}) = \sum_{p=1}^l \sum_{j=1}^m \sum_{i=1}^n Cr_i \cdot IUC_{ijp} \cdot Q_{ijp} \quad (27)$$

$$F_2(Q_{ijp}) = \sum_{p=1}^l \sum_{j=1}^m |CT_p^{moy\_eff} - CT_{jp}^{ind\_eff}| \quad (28)$$

With:

$$CT_p^{moy\_eff} = \frac{CT_p^{tot\_eff}}{NB_{op}}, \quad \forall p \in L$$

$$CT_p^{tot\_eff} = \sum_{i=1}^n \frac{Q_{ip}}{Cp_i \times RI_{ip}^{moy} \times TD_{moy}}, \quad \forall p \in L$$

$$CT_{jp}^{ind\_eff} = \sum_{i=1}^n \frac{Q_{ijp}}{Cp_i \times RI_{ijp} \times TD_{moy}}, \quad \forall j \in M; \forall p \in L$$

$RI_{ijp}$ : The performance of the individual (j) in carrying out the activity (i) during the period (p), It is calculated from the values of the two indicators (WP) and (EQ):  $RI = WP \times EQ$ ;

$RI_{ip}^{moy}$ : This is the average of the performance of workers executing the activity (i) during period (p), it is calculated as follows:

$$RI_{ip}^{moy} = \sum_{j=1}^m \frac{RI_{ijp}}{NB_{op \text{ executing the activity}(i)}}, \quad \forall i \in N; \forall p \in L;$$

$TD_{moy}$ : Workstation availability rate.

$$F_3(Q_{ijp}) = \sum_{j=1}^m \sum_{i=1}^n \max(0; IUC_{ij \text{ finish date}} - IUC_{i \text{ target}}) \quad (29)$$

At the end of the identification of the criteria to optimize, the objective function of the problem can be represented as the sum of the three expressions:

$$\begin{aligned} & \text{Min} \sum_{p=1}^l \sum_{j=1}^m \sum_{i=1}^n Cr_i \cdot IUC_{ijp} \cdot Q_{ijp} \\ & + \sum_{p=1}^l \sum_{j=1}^m |CT_p^{moy\_eff} - CT_{jp}^{ind\_eff}| \\ & + \sum_{j=1}^m \sum_{i=1}^n \max(0, IUC_{ij \text{ finish date}} - IUC_{i \text{ target}}) \end{aligned} \quad (30)$$

### 5.3. The model constraints:

Individuals' allocation constraints: these constraints insure that, for each worker and at each period, the individual workload is always lower than or equal to the available working hours  $HD_{jp}$ :

$$CT_{jp}^{ind\_eff} \leq HD_{jp} \quad \forall j \in M; \forall p \in L \quad (31)$$

Quantitative constraints: these constraints insure that for each activity, the total produced quantity for the current period are always equal to the demanded quantity:

$$\sum_{j=1}^m \sum_{i=1}^n Q_{ijp} = Qd_{ip} \quad \forall p \in L \quad (32)$$

These constraints insure that, for each activity, the quantity assigned should be greater than or equal to the minimum lot size:

$$Q_{ijp} \geq Q_{ls,i} \quad \forall i \in N \quad (33)$$

## 6. GENETIC ALGORITHM

This work deals with reducing assignment cost and developing versatility. The proposed formulation is considered as a difficult optimization problem. Genetic algorithms are part of the class of evolutionary algorithms. With this type of method, it is not a question of finding an exact solution but it is a matter of finding a good feasible solution within a reasonable calculation time. The goal of these genetic algorithms is to optimize a function-objective called fitness. They manipulate a set of feasible solutions, called (population). The genetic algorithm starts with a generation of a set of individuals (feasible solutions) in a random way to form the initial population. Subsequently, the individuals of the population are evaluated and are ranked in descending order. Then, a subset of parents is selected to favor the best individuals. From this set, a group of children is generated by crossing and mutating mechanisms. The selection and reproduction phases generate a new population



of individuals, which are likely to perform better than those of the previous generation. Individuals from the reproductive phase will be inserted by a replacement method into the new population. From generation to generation, the performance of individuals in the population increases. The process is repeated until a defined stop criterion is met.

**6.1. Initial population representation**

The problem-solving process of genetic algorithms begins with the identification of chromosome representation. In the present article, we describe a genetic algorithm with a matrix form to solve this multi-period assignment problem with multi-skilled workforce. The proposed genetic algorithm is based on a direct encoding of the problem. We will introduce the initial population by generating an initial random chromosome of feasible solutions to form a parent solution, followed by obtaining new solutions and forming new parent through an iterative process. As shown in Figure 5.1, a solution is made up of a matrix form of (n) columns, where (n) is the number of activities and (m) lines, where (m) is the number of workers. This structure is duplicated for each period. Each of the chromosome elements has a value from  $Q_{ls,i}$  to  $Q_{dp}$  or  $Q_{ijp} = 0$ .

		A1	A2	A3	A4	A5
P1	Op1	Q <sub>111</sub>	Q <sub>211</sub>	Q <sub>311</sub>	Q <sub>411</sub>	Q <sub>511</sub>
	Op2	Q <sub>121</sub>	Q <sub>221</sub>	Q <sub>321</sub>	Q <sub>421</sub>	Q <sub>521</sub>
	Op3	Q <sub>131</sub>	Q <sub>231</sub>	Q <sub>331</sub>	Q <sub>431</sub>	Q <sub>531</sub>
	Op4	Q <sub>141</sub>	Q <sub>241</sub>	Q <sub>341</sub>	Q <sub>441</sub>	Q <sub>541</sub>
P2	Op1	Q <sub>112</sub>	Q <sub>212</sub>	Q <sub>312</sub>	Q <sub>412</sub>	Q <sub>512</sub>
	Op2	Q <sub>122</sub>	Q <sub>222</sub>	Q <sub>322</sub>	Q <sub>422</sub>	Q <sub>522</sub>
	Op3	Q <sub>132</sub>	Q <sub>232</sub>	Q <sub>332</sub>	Q <sub>432</sub>	Q <sub>532</sub>
	Op4	Q <sub>142</sub>	Q <sub>242</sub>	Q <sub>342</sub>	Q <sub>442</sub>	Q <sub>542</sub>
P3	Op1	Q <sub>113</sub>	Q <sub>213</sub>	Q <sub>313</sub>	Q <sub>413</sub>	Q <sub>513</sub>
	Op2	Q <sub>123</sub>	Q <sub>223</sub>	Q <sub>323</sub>	Q <sub>423</sub>	Q <sub>523</sub>
	Op3	Q <sub>133</sub>	Q <sub>233</sub>	Q <sub>333</sub>	Q <sub>433</sub>	Q <sub>533</sub>
	Op4	Q <sub>143</sub>	Q <sub>243</sub>	Q <sub>343</sub>	Q <sub>443</sub>	Q <sub>543</sub>

Figure 5.1: The solution representation

**6.2. Generating an initial population**

In this step, an initial population must be generated, where each chromosome represents a solution of the problem. The procedure we used to

generate the initial population of individuals is a guided random generation of (P\_size) individuals. This random generation is oriented in such a way that for each activity and for each period, the sum of the quantities allocated to the different operators is equal to the quantity demanded of this activity ( $Q_{d,i}$ ). For each period (p) and each activity (i), the generation of solutions of the initial population must respect the following constraints:

$$\sum_{j=1}^m \sum_{i=1}^n Q_{ijp} = Q_{d,ip}, \quad \forall i \in N, \quad \forall p \in L$$

$$Q_{ijp} \geq Q_{ls,i}, \quad \forall i \in N$$

In this phase, each allocation solution does not necessarily respect the capacity constraint. In other words, we accept the violation of capacity constraints when generating the initial population. This capacity constraint will be monitored during the evaluation phase of the objective function.

**6.3. Evaluation function**

The evaluation phase consists of calculating the fitness of each individual within the population. The main objectives of this work, expressed by the three functions, can be calculated as described above. Despite the genetic algorithms being usually implemented to maximize an objective function [7], our main focus here is to minimize the objective function so that the minimum value will correspond to the best individual. The next step is to determine the fitness of each chromosome. The fitness expression is composed mainly of four terms, as shown in (34). The first three terms represent the basic objective function to minimize. The fourth term allows checking the degree of feasibility of the solutions with respect to the available working hours ( $HD_{jp}$ ). Indeed, the three first terms of the evaluation function are different; we must first normalize each term. The aim of normalization methods is to individually transform each term of the evaluation function to make them homogeneous before combining them. After normalization, the three first terms can be added with an importance weight ( $\varphi_t$ ) associated to each term. As a result, we obtain the following evaluation function:

$$F_{\text{évaluation}} = \varphi_1 F_1^{\text{Nor}} + \varphi_2 F_2^{\text{Nor}} + \varphi_3 F_3^{\text{Nor}} + F_4 \tag{34}$$

With,

$$\sum_{t=1}^{t=3} \varphi_t = 1, \varphi_t \geq 0$$

$$F_4 = V \cdot C_{HD} \cdot \sum_{p=1}^1 \sum_{j=1}^m \max(0, CT_{jp}^{ind\_eff} - HD_{jp})$$

The expression  $\max(0, CT_{jp}^{ind\_eff} - HD_{jp})$  measures for each period (p) the degree of violation of the available capacity of the actor (j). The factor (V) is a binary variable expressing the capacity constraint violation state: V = 1 for constraint violation and V = 0 for constraint satisfaction.

$C_{HD}$  is a virtual penalty cost related to any workload that would finish outside the available working hours.

Using this method of normalization and weighting allows us first to favor the possible solutions and to control the compromise between the costs incurred and the development of versatility.

#### 6.4. Selection phase

The selection phase is the determination of individuals from the current population for the reproduction process. The method used is a tournament selection with a tournament size equal to a probability of population size. The selection of a number (k) of individuals is done randomly, then, among this group of individuals, the two best individuals are selected according to the value of their fitness. The other individuals who participated in the tournament are handed over to the population. This procedure is illustrated in Figure 5.2. This method greatly improves the genetic algorithms, because it allows favoring the best chromosomes against the worst ones and ensures no loss among the best individuals found.

#### 6.5. Crossover operator

To obtain new individuals (children) from the selection of two parents, we will use the 1-point crossover operator at the level of the columns of the matrix corresponding to the activities, for each period. This crossing will be carried out as follows (Figure 5.3):

#### 6.6. Mutation operator

Individuals obtained from the crossover phase will undergo the mutation operation. The

mutation operator used is the reciprocal exchange operator. In our approach, this mutation operator is used in two steps. This logic is illustrated in Figure 5.4.

#### 6.7. Insertion operator

Insertion operator is used to improve the overall performance of the population. This insertion allows eliminating the poorest chromosomes from the population. Indeed, individuals that are generated randomly are sorted according to their fitness value in a descending order (in the case of minimization). In our approach, we adopted as type of replacement the Steady-state method.

#### 6.8. Stopping condition

The implementation of genetic algorithms requires the definition of a predetermined stopping. In our approach, we define one stopping criterion, and when it is valid, the exploration will be stopped. The criterion simply depends on the number of generations that were produced. When this maximum number of generations has been run, then the termination procedure occurs. The choice of the maximum number of generations is related to the evolution of the objective function. If the evolution of the fitness no longer seems to evolve, the process is considered to have converged.

### 7. Illustrative example

We applied the proposed model on an example of parallel resources which are mainly operators with high added-value. The problem is composed of 8 activities (index A), 4 individuals (index Op), and 4 periods (index P), as shown in tables 7.1 and 7.2.

To describe this problem we need two data sets. The first one, related to the activities to be processed, indicates the theoretical production rates and quantities ordered by period.

Table 7.1: Quantity ordered by period of each activity (in units)

$Qd_{ip}$	A 1	A 2	A 3	A 4	A 5	A 6	A 7	A 8
P 1	200	190	210	170	200	170	200	180
P 2	180	150	250	200	220	190	190	190
P 3	210	240	160	150	180	230	190	190

P 4	170	200	170	220	190	180	170	200											
										Op3	0,35	0,24	0,45	0,25	0,33	0,52	0,32	0,26	
										Op4	0,25	0,23	0,23	0,21	0,26	0,33	0,36	0,42	

Table 7.2: Theoretical production rate

	A 1	A 2	A 3	A 4	A 5	A 6	A 7	A 8
$Cp_i$	13	15	18	11	16	18	15	20

The second set of parameters is related to the company: there are different values on the working hours of each individual and the production costs as illustrated by table 7.3. The weekly working hours should not exceed 44 hours.

Table 7.3: The inherent costs of production

	A	A	A	A	A	A	A	A
	1	2	3	4	5	6	7	8
Cr	50	51	58	73	63	50	70	69
$Cmp_{1\ unité}$	25	31	31	36	36	33	30	37
$\alpha = Cmp_{1\ unité}/Cr$	0,5	0,6	0,5	0,4	0,5	0,6	0,4	0,5
	5	1	3	9	7	6	3	4

We also assume that at the start date of the assignment process, the individual underperformance coefficient (IUC) in the different activities are those shown in table 7.4:

Table 7.4: The initial individual underperformance coefficient (IUC) in the different activities

		A 1	A 2	A 3	A 4	A 5	A 6	A 7	A 8
WP	Op1	0,76	0,71	0,67	0,9	0,72	0,88	0,76	0,62
	Op2	0,66	0,65	0,67	0,89	0,86	0,74	0,83	0,87
	Op3	0,71	0,73	0,7	0,84	0,85	0,61	0,75	0,88
	Op4	0,81	0,74	0,85	0,82	0,68	0,77	0,83	0,68
EQ	Op1	0,85	0,89	0,93	0,86	0,8	0,85	0,81	0,93
	Op2	0,94	0,82	0,93	0,8	0,92	0,81	0,8	0,84
	Op3	0,91	0,95	0,85	0,91	0,85	0,83	0,94	0,9
	Op4	0,92	0,94	0,91	0,93	0,94	0,85	0,84	0,86
CR	Op1	0,9	0,92	0,88	0,91	0,9	0,95	0,89	0,92
	Op2	0,93	0,9	0,97	0,93	0,91	0,95	0,9	0,9
	Op3	0,86	0,89	0,85	0,9	0,9	0,84	0,82	0,87
	Op4	0,9	0,92	0,91	0,94	0,92	0,93	0,9	0,88
IUC	Op1	0,38	0,31	0,32	0,28	0,48	0,27	0,47	0,31
	Op2	0,28	0,47	0,26	0,37	0,21	0,39	0,43	0,33

We recall that the closer its value is to 0, the better is the individual competence level. Furthermore, we assume that the learning rate and forgetting rate are the same for all individuals, and which are respectively 80%, corresponding to the parameter ( $r_{i,j}$ ) and 90% corresponding to the parameter ( $k_{i,j}$ ). We assume that the (IUC) is calculated for each individual at the beginning of each period based on previous assignments, and it remains constant during the same period. To solve the problem, we must define the company's preoccupations, namely:

- Case 1: Reduce the losses suffered by the underperformance of the workforce, therefore, use of the most competent individuals. This will not expand the versatility of operators.
- Case 2: Develop the versatility of the actors, the thing that will lead to additional costs,
- Case 3: Seek a compromise between these two extreme cases.

7.1. Case 1: minimization of the extra cost

First, we tried to solve the problem with the minimum cost. The assignment solution is summarized in table 7.5, highlighting the amount allocated to each candidate per period for the different activities.

Table 7.5: The optimal solution (minimizing cost incurred)

		A1	A2	A3	A4	A5	A6	A7	A8
P 1	Op1	0	0	98	119	0	61	0	98
	Op2	62	0	57	0	119	109	52	0
	Op3	0	115	0	51	0	0	87	82
	Op4	138	75	55	0	81	0	61	0
	Total	200	190	210	170	200	170	200	180
P 2	Op1	53	0	51	148	0	105	0	0
	Op2	58	0	76	0	142	85	53	0
	Op3	0	71	0	0	78	0	78	190
	Op4	69	79	123	52	0	0	59	0
	Total	180	150	250	200	220	190	190	190
P 3	Op1	0	54	74	96	0	70	0	72
	Op2	82	0	0	54	124	57	0	62

	Op3	58	61	0	0	56	0	134	56
	Op4	70	125	86	0	0	103	56	0
	Total	210	240	160	150	180	230	190	190
P 4	Op1	0	87	0	121	0	86	0	92
	Op2	170	0	67	0	77	0	0	58
	Op3	0	0	0	99	113	0	72	50
	Op4	0	113	103	0	0	94	98	0
	Total	170	200	170	220	190	180	170	200

The cost allocation in this case is equal to 64861 (currency unit). Furthermore, the assignment solution respects the constraint of availability of each individual. As shown in figure 7.1, the workload assigned to each candidate is less than its weekly working hours. Thus, the solution respects the uniform load distribution and the operators have more or less the same workload at each period.

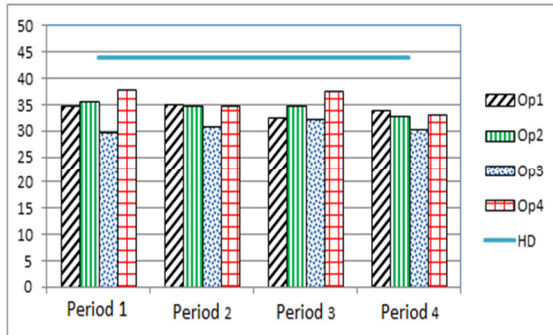


Figure 7.1: The workloads distribution of the different actors

However, this solution does not promote versatility. On the other hand, the company loses skills of its operators because of the effect of oblivion. This is shown in the figure 7.3, which shows the evolution of the individual underperformance coefficient (IUC).

**7.2. Case 2: minimizing costs associated with individual performance in order to enhance the versatility**

In this case, we tried to solve the problem with skill improvement. The assignment solution is summarized in table 7.6, highlighting the amount allocated to each candidate per period for the different activities.

Table 7.6: The optimal solution (skill improvement)

		A1	A2	A3	A4	A5	A6	A7	A8
Period1	Op1	0	94	140	0	0	93	81	0
	Op2	0	0	0	70	66	77	54	116
	Op3	109	0	70	0	134	0	65	0
	Op4	91	96	0	100	0	0	0	64
	Total	200	190	210	170	200	170	200	180
Period2	Op1	180	65	59	0	0	0	54	0
	Op2	0	85	0	92	52	106	0	58
	Op3	0	0	129	108	115	0	0	59
	Op4	0	0	62	0	53	84	136	73
	Total	180	150	250	200	220	190	190	190
Period3	Op1	108	0	52	64	0	96	0	62
	Op2	0	58	50	86	106	0	53	0
	Op3	102	78	58	0	0	63	85	0
	Op4	0	104	0	0	74	71	52	128
	Total	210	240	160	150	180	230	190	190
Period4	Op1	57	94	0	0	77	0	113	0
	Op2	113	0	0	82	0	71	57	0
	Op3	0	0	83	0	113	109	0	145
	Op4	0	106	87	138	0	0	0	55
	Total	170	200	170	220	190	180	170	200

The cost allocation in this case is equal to 79994 (currency unit). Like in the first case, the assignment solution respects the constraint of availability of each individual. As shown in figure 7.2, the workload assigned to each candidate is less than its weekly working hours. Thus, the solution respects the uniform load distribution and the operators have more or less the same workload at each period.

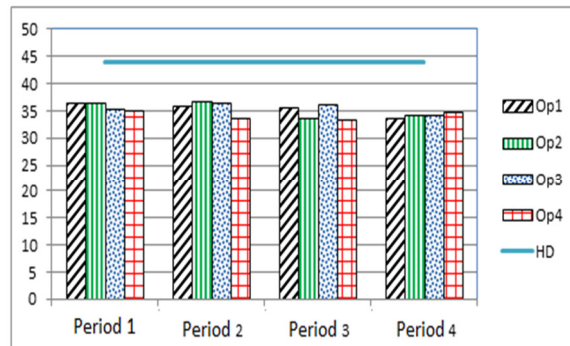


Figure 7.2: Distribution of workloads of the different actors

This solution helps improve versatility. As we can see, the performance of all operators has been indeed improved. This is shown in the figure 7.3, which shows the evolution of the underperformance coefficient.

### 7.3. Synthesis of the two cases

The curves of the figures (Figure 7.3 and Figure 7.4) show the evolution of the average global improvement of the individual underperformance coefficient (IUC) for both cases. For the second case, we observe that the average overall competence rate has improved significantly by (+ 29.13%), as shown in figure 7.3 (change from 12.7% to 16.4%). We can also see that the curve flattened (figure 7.4), this allows to absorb and to minimize the differences between the operators. However, on the other hand we observed an increase in the cost incurred by (+ 23.3%), as shown in Figure 7.5. Improving the level of individual competence has a cost.

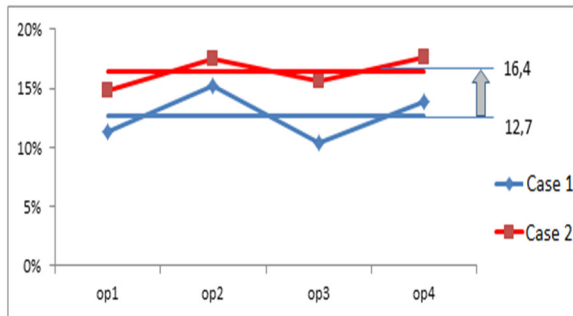


Figure 7.3: Evolution of the average global improvement of the individual underperformance coefficient (IUC)

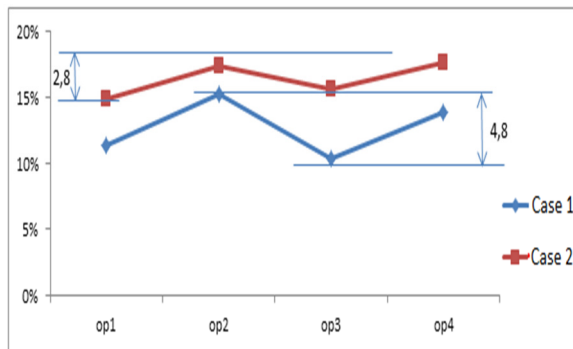


Figure 7.4: Behavior of the change in the individual underperformance coefficient (IUC)

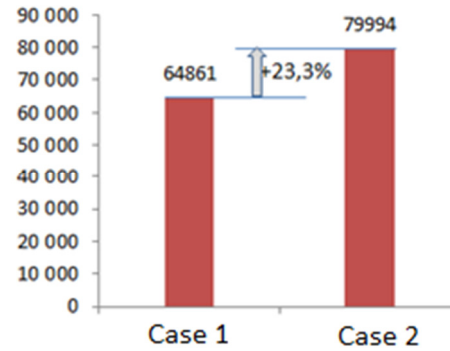


Figure 7.5: Evolution of the cost incurred

Regarding the cost related to the objective of improving competencies by practice, we recall that it is calculated from the difference between the IUC which we hope to get at the end. The IUC values will be obtained at the end of the simulation. The competency goals at the beginning of the simulation are an input data. The solution obtained by the genetic algorithm helps to develop the competency of each individual. This solution, obtained after four periods of simulation, allowed improving the competency of the four operators. However, this development of competency directly causes an increase in the cost incurred by the company.

### 7.4. Case 3: search of a compromise between reducing the cost incurred and improving individual performance

Recall that in our case study, we try to solve a multi-objective problem; the majority of optimization algorithms used for their solution are single-objective optimization algorithms. The functions of each objective are combined into a single objective function using a weighted sum of all terms. Weights are known as factors of importance and are considered as a measure of the significance of each objective in the optimization process. Multi-objective optimization requires a decision-making process because there is not a single solution but a set of non-dominated solutions. Non-dominated solutions provide information about the compromise between objectives. This compromise is described by the shape of the Pareto front. A convex part representative of the optimal Pareto solutions can be plotted by running the optimization algorithm several times with different weighting values. The complexity of the Pareto front along with the combinatorial complexity increases rapidly if the



number of objectives to be considered is greater than two. In our case, we will consider two objectives: the first objective is to give information about the cost incurred expressed by (F1), the second is to give information on the evolution of the individual performance expressed by (F3). The other two objectives expressed by the terms (F2) and (F4) allow to control the distribution of the workload and the constraint of the legal working hours. Figure 7.6 illustrates the density of the points forming the Pareto front.

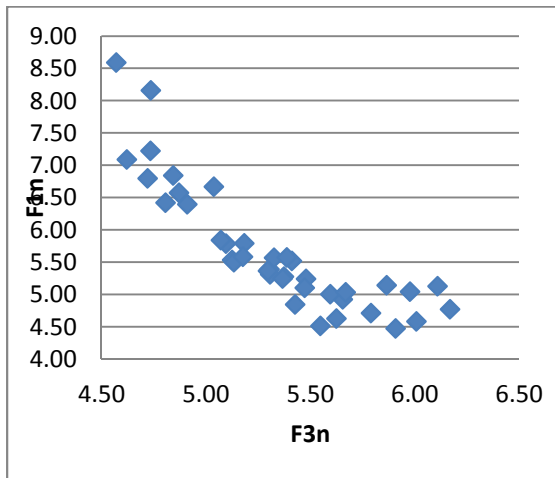


Figure 7.6: Density of points forming the Pareto front

From figure 7.6, we can see that there is a strong compromise between objective (F1) and objective (F3). The lower the value F1 is, the greater the corresponding F3 value becomes. As we can see, there is not a single solution but a set of solutions that provide the compromise between the two objectives. This compromise is described by the shape of the Pareto front on the basis of which decision-making can be made. The proposed method provides a tool for the multi-period assignment problem in order to minimize the costs incurred and to take into account the operators' skills objectives.

## 8. CONCLUSION

In this article, we presented a mathematical model and a genetic algorithm approach to solve the workforce multi-periods allocations problem. The scientific difficulty of this problem resides on one hand, in its formulation (problem of multi-period assignment, choice of an indicator of individual competence, choice of a

model of competences evolution and choice of the fitness expression) and on the other hand in its resolution, it is a non-linear problem. The aim of this proposed formulation is to take account of individual competences, their dynamic development and the equitable distribution of the workload. Taking these three factors into account, led us to make changes to the expression of the objective function. For this purpose, we have incorporated an individual performance coefficient (IUC) in the proposed model in which a mathematical expression of (IUC) has been proposed. In addition to the explicit integration of the notion of competence through the use of the coefficient (IUC), two penalty costs were added, the first cost is due to the dissatisfaction of the work distribution constraints and the second cost is related to non-respect of versatility. Considering the both constraints of the equitable distribution of the workload and the versatility in the assignment problem, leads to a rotation in the execution of all activities, which promotes the learning of human resources and developing the flexibility of individuals.

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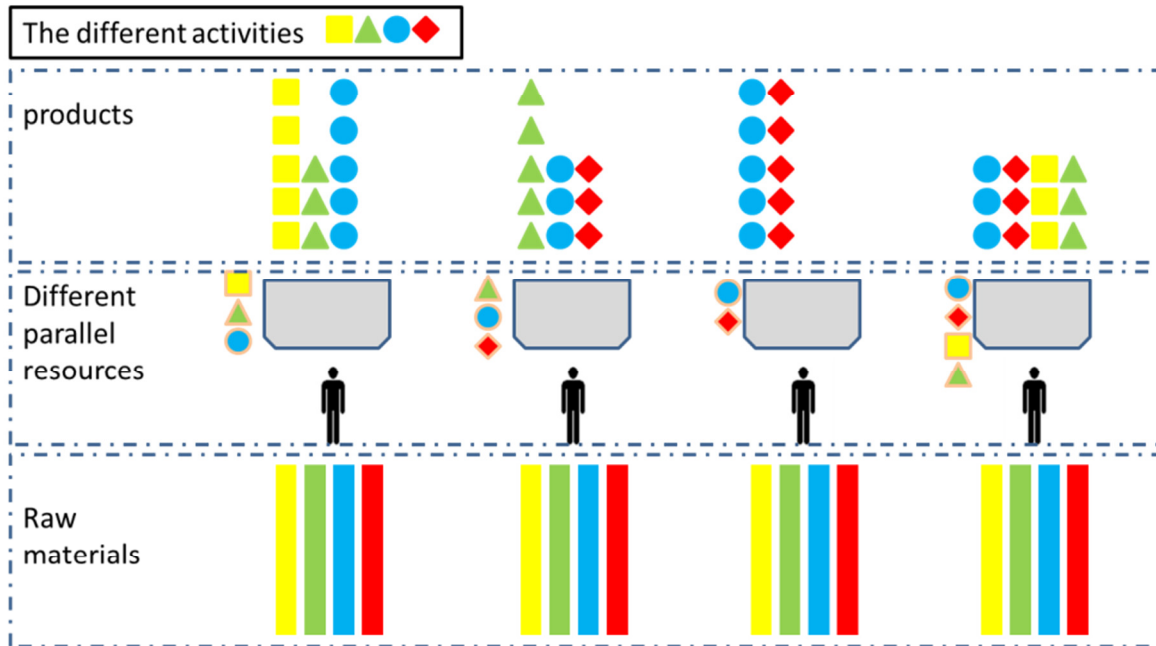


Figure 2.1: Illustration of the study context

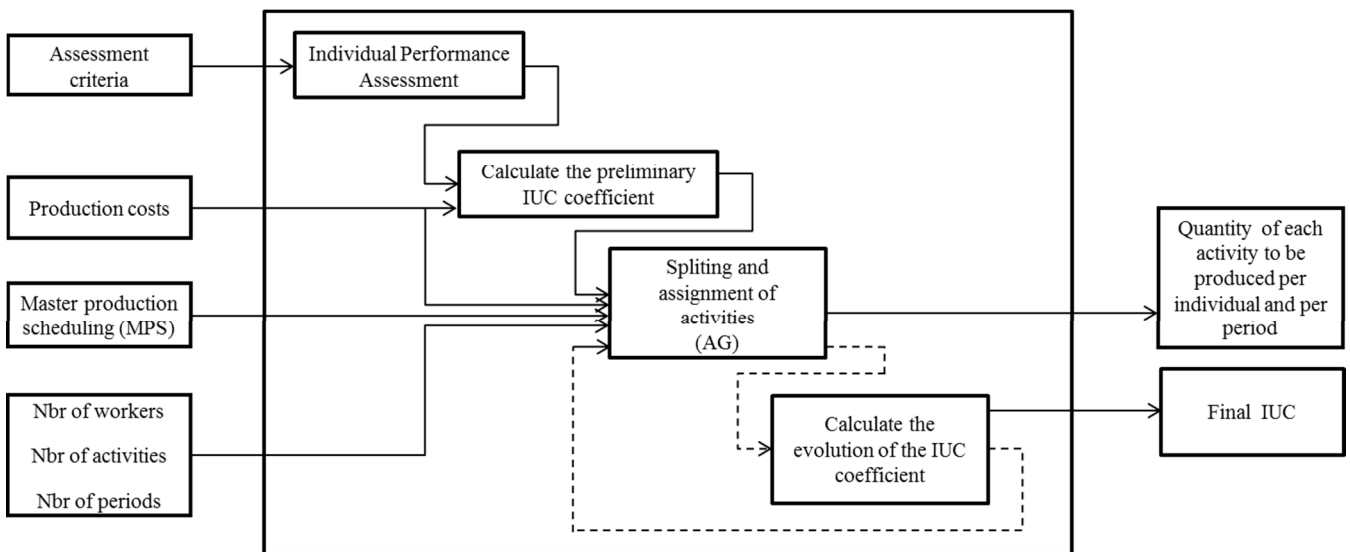


Figure 2.2: The principle of assignment logic

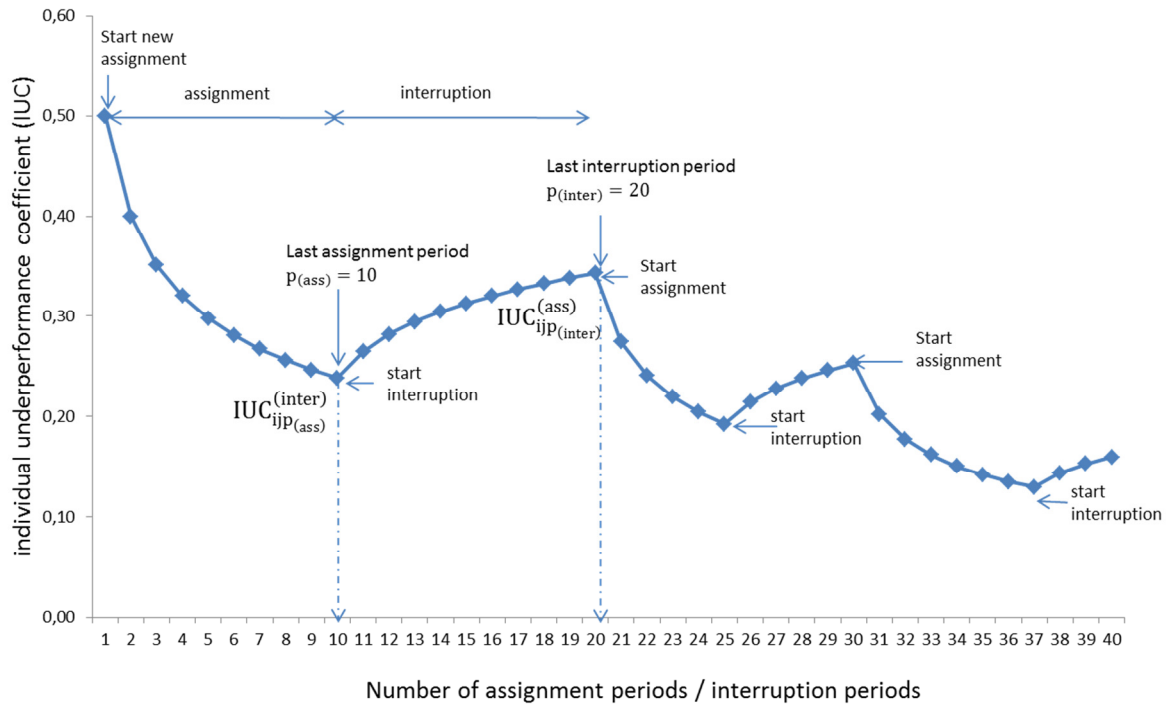


Figure 3.1: Illustration of the effect of the learning-forgetting curve



Figure 5.4: Illustration of the mutation operator