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# An Optimizing Approach for Multi Constraints Reassignment Problem of Human Resources

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| Article Info | ABSTRACT |
|---|---|
| | This paper presents an effective approach to optimize the reassignment of Human Resources in the enterprise that is formed by several units of productions to take into consideration the human characteristics. This approach consists of two steps; the first step is to formalize the studied problem that is practically take the form of the generalized assignment problem (GAP) known as NP-hard problem. Additionally, the variables in the formulation of our problem are interlinked by certain constraints. These two proprieties can to justify the important complexity of this problem. The second step is focused to solve this complex problem by using the genetic algorithm. We present the experimentally result for justifying the validity of the proposed approach. So, the solution obtained allowed us to get an optimal assignment of personnel that can lead to improve the average productivity or ratability or at least ensure its equilibration within sites of enterprise.<br><br> |

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## 1. INTRODUCTION

The human resources can be seen as a source of sustained competitive advantage for organizations and a major asset in their strategic reorientation. Furthermore, for a more dynamic management of these resources, the managers of the organizations of production attempt to identify suitable profiles to maintain and develop their productivity. Given that the theory based on human resources show that the good productivity in the enterprises can be resulted in the way how the assignment of human resources is performed [1]-[2]. The personnel reassignment can be considered as an important factor to dispose the human resources quality that can be capable to contribute for meeting the desired objective by the manager and its serves to reduce the recruitment costs. In the large enterprises or administrations decomposed by several production units and distributed across multiple geographical sites, this reassignment processes or processes mobility can to lead to improve or to maintain the productivity within the production units and to motivate the agents.

Generally, each agent occupy a post in the original site and want to change this site another voluntarily or by redeployment, is identified by individual weight calculated by basing socio-professional criteria function. This weight can be grouped the competency, the profitability and the individual performance …etc. In order to optimize the best repartition of personnel and to reaching the objectives fixed, the managers must to dispose an optimizing tools based on a formal model by integrating these specific weights and mobility constraints [3].

The work [4] addresses a theoretical model based for empirical facts on repartition of workers across clusters with different labor productivity. Its key idea is to assume that there are restrictions on

capacity of workers for clusters with high productivity. The work [5] is focused to find a solution for assignment problem by respecting the different constraints relative to labor regulations and a constraint relative to multiple sites, balance the workload over employees but not addressing in the problem the impact these displacements of human resources on the productivity in the sites and not taking into account the constraints related to cyclic assignment and conservation of posts.

Generally, Our work is the complements of our previous works [1]-[3], is focused on diversity of possible forms and relationship between the reassignment which also we label the mobility of human resources, and his positively impact on the productivity in the enterprise basing on the specific weight by respecting of several constraint. The formulation developed in this work illustrate that this problem can be classified as constrained combinatorial optimization problems and can be taken a generalized assignment problem form known as NP-hard problem [6] and its practically similar to multi index assignment problems (MIAPs) [7].

To resolve this problem, we are interested to implement the genetic algorithms which can be characterized by an efficiency to solve NP-hard problems. Additionally, the optimal solution obtained must be ensured the improvement the average productivity for each unit of production through the right choice of parameters of this problem. For this, For this, the genetic operators used for starting the genetic algorithm are uniform selection, operator Matrix crossing *UX* (Uniform Crossover) [8], Operator Matrix mutation *HPRM* that is combined between uniform mutation [9] and *HPRM* operator [10]. We call again that the operators *UM* and *HPRM* have provided encouraging results in solving the traveling salesman problem (*TSP*) which is an NP-complete problem [10].

This paper is organized as follows: firstly we present the mathematical formalism modeling this approach and evaluate its complexity. Secondly we will implement genetic algorithms to find the optimal repartition of human resources to improving the average productivity and to satisfying it. Computational results obtained on randomly generated instances are reported to evaluate the validity approach.

## 2.    FORMULATION OF THE PROBLEM

### 2.1.  Representation of the Problem

This new work is considered as the complement the work presented in paper [1]-[2]. In addition, we consider that the enterprise is decomposed into several production units $E_j$ with $j \in [1, NU]$ geographically distributed. The number of employee $\widetilde{N}_{jk}$ wishing to displace from a unit $E_j$ to another $E_k$ is symbolized by $E_{jk}^i$ and is possessed the specific weight $W_{jk}^i, i \in [1, \widetilde{N}_{jk}]$. The set of this group is:

$$E_{jk} = \left\{ E_{jk}^1, E_{jk}^2, E_{jk}^i, \dots, E_{jk}^{\widetilde{N_{jk}}} \right\}$$

Ket:
- $\widetilde{N}_j = \sum_{k=1}^{NE} \widetilde{N_{jk}}$ is the number of the candidate's employees to reassign from $E_j$ to $E_k$. ($\forall j \in [1, NU]$ ).
- $X_{jk}^i$ is the bivalent variables, the employee is reassigned from one unit $E_j$ to another $E_k$ if $X_{jk}^i = 1$ and 0 otherwise.

Initially, the all candidates wishing to mobilize must be verified the objective constraint given by:

$$\bar{W}_k \geq \alpha_k \bar{W}_k^0 \tag{1}$$

- $\alpha_k$ is the tolerance coefficient parametrizing this constraint .
- $\bar{W}_k$  is the average weight engendered by candidates moved to the unit $E_k$.
- $\bar{W}_k^0$ is the average weight of candidates initially worked in the unit $E_k$.

For the problem studied, we can list several constraints:

### 2.2.  Cost constraint

We assume that the posts can be occupied by an agent ($X_{kj}^i = 1$) which consumes a variety of the enterprise resources $r_{ij}^k$. The global consumed resources is limited by the capacity resource $R_k$ . The expression of resource constraint as follows:

$$\sum_{\substack{j=1 \\ j \neq k}}^{NU} \sum_{i=1}^{\widetilde{N}_{jk}} r_{ij}^{k,} X_{ijk}^k \leq R_k \tag{2}$$

### 2.3. Equilibrium constraint of posts

This constraint explain that the number of occupied posts by the candidates reallocated from department $E_j$ to unit $E_k$ must be equal the number of vacated posts by candidates which leave the same unit. The expression of this constraint is expressed by:

$$\sum_{\substack{j=1 \\ j \neq k}}^{NU} \sum_{i=1}^{\tilde{N}_{jk}} X_{jk}^i = \sum_{\substack{k=1 \\ j \neq k}}^{NU} \sum_{i=1}^{\tilde{N}_k} X_{kj}^i \tag{3}$$

### 2.4. Capacity constraint

The capacity constraint requires which the number $N_k$ of agent reassigned to the department $E_k$ is limited by an $C_k$ imposed by the managers; the expression is given as follows:

$$\sum_{\substack{j=1 \\ j \neq k}}^{NS} \sum_{i=1}^{\tilde{N}_{jk}} X_{jk}^i \leq C_k \tag{4}$$

when the resources of the posts are identical, the resource constraint can be reduced capacity.

### 2.5. Priority constraint

These weights are the elements of the sub-matrix $\beta^{k,\alpha_k}$:

$$if \ W_{jk}^i \leq W_{j'k}^i \ \textbf{and} \ X_{jk}^i = 1 \ then \ X_{j'k}^i = 1 \ ;$$

$$i \leq l \ ; \ 1 \leq i \leq max(\tilde{N}_k); \ j \neq k$$

Or:

$$X_{jk}^l \left( \sum_{i=1}^l X_{jk}^i - 1 \right) = 0 \ \forall \ l \in \left[ 1, \tilde{N}_k \right] \tag{5}$$

### 2.6. Uniqueness constraint

Another constraint can be added to the other constraints that is the uniqueness constraint which explains a candidate can't have two posts simultaneously in two departments $E_k$:

$$\sum_{k=1}^{NE} X_{ijk} \leq 1 \ \forall \ i \in \left[ 1, \tilde{N}_{jk} \right], \forall \ j \in [1, NE] \tag{6}$$

Based on the work [1], the number of candidate reassigned to the unit of production $E_k$ can be given by:

$$N_k = \sum_{\substack{j=1 \\ j \neq k}}^{NU} \sum_{i=1}^{\tilde{N}_{jk}} X_{jk}^i \tag{7}$$

The global weight engendered by the assigned agents is given by:

$$W_k^{global} = \sum_{\substack{j=1 \\ j \neq k}}^{NU} \sum_{i=1}^{\tilde{N}_{jk}} W_{jk}^i X_{jk}^i \tag{8}$$

The average weight associated with $N_k$ assigned agents is given by:

$$\overline{W}_k = \frac{W_k^{global}}{N_k} \tag{9}$$

Let :

$$\overline{W}_k = \frac{1}{N_k} \sum_{\substack{j=1 \\ j \neq k}}^{NU} \sum_{i=1}^{\tilde{N}_{jk}} W_{jk}^i \tag{10}$$

The combination of equation (1) and (9) is given by:

$$\sum_{\substack{j=1 \\ j \neq k}}^{NU} \sum_{i=1}^{\widetilde{N}_{jk}} (W_{jk}^i X_{jk}^i - \alpha_k \overline{W}_k^0 X_{jk}^i \ ) \geq 0$$

If we put: $\beta_{jk}^{i\alpha_k} = (W_{jk}^i - \alpha_k \overline{W}_k^0 \ )$, we will construct a sub matrix assignment noted $\beta^{k,\alpha}$ or:

$$\beta_k^{\alpha_k} = \left\{ \beta_{jik}^{\alpha_k} / 1 \leq j \leq NU; \ 1 \leq i \leq max(\widetilde{N}_{jk}); j \neq k \right\}$$

Similarly, we construct a sub-matrix $X_k$ such that:

$$X^k = \left\{ X_{jk}^{i,\alpha_k} / 1 \leq i \leq NU; \ 1 \leq j \leq max(\widetilde{N}_{jk}); j \neq k \right\}$$

We assume that the tolerance coefficient $\alpha_k$ associated with unit production $E_k$ are equals. So, the global formulation of this problem is written as follows:

$$Max(F^a) = Max \sum_{k=1}^{NU} Trace(\beta_k^{\alpha_k} X_k ) \qquad (11) \qquad (11)$$

Under the constraints:

$$\begin{cases} Trace(\beta_k^{\alpha_k} X_k) \geq 0 \forall & k \in [1, NU] \\ X_{jk}^i (\sum_{i=1}^l X_{jk}^i - l) = 0 & \forall l \in [1, \widetilde{N}_{jk}] \\ \sum_{\substack{j=1 \\ j \neq k}}^{NU} \sum_{i=1}^{\widetilde{N}_{jk}} X_{ij}^k \leq C_k & \forall k \in [1, NU] \\ \sum_{\substack{j=1 \\ j \neq k}}^{NU} \sum_{i=1}^{\widetilde{N}_{jk}} r_{jk}^i X_{jk}^i \leq R_k & \forall k \in [1, NU] \\ \sum_{k=1}^{NU} X_{jk}^i \leq 1 & \forall i \in [1, \widetilde{N}_{jk}], \forall j \in [1, NU] \end{cases} \qquad (12)$$

The weight generated by $N_k$ candidates reassigned to the unit $E_k$ is:

$$W_k^+ = \sum_{\substack{j=1 \\ j \neq k}}^{NU} \sum_{i=1}^{\widetilde{N}_{jk}} W_{jk}^i X_{jk}^i \qquad (13) \qquad (13)$$

The weight generated by the same number $N_k$ of candidates moved from the unit $E_k$ is:

$$W_k^- = \sum_{\substack{j=1 \\ j \neq k}}^{NU} \sum_{i=1}^{\widetilde{N}_{jk}} W_{kj}^i X_{kj}^i \qquad (14) \qquad (14)$$

The improvement weight by the reassignment processes associated to the unit $E_k$ is:

$$\Delta W_k = W_k^+ - W_k^-$$

$$\Delta W_k = \left(\sum_{i=1}^{N_k} W_k^i\right)_{in} - \left(\sum_{i=1}^{N_k} W_k^i\right)_{out} \qquad (15) \qquad (15)$$

Generally, within unit of production, this gap expresses the improving global weight if $\Delta \boldsymbol{W_k} > 0$ and he explain the equilibrium of this global weight if $\Delta \boldsymbol{W_k} = \boldsymbol{0}$.

## 3.    COMPLEXITY OF THE PROBLEM

The assignments of candidates to the units of production are linked. In addition, the formulation of the problem is practically similar to the mathematical model for the Generalized Assignment Problem (GAP) that it's NP-hard [11] and can be considered such as multi index assignment problems (MIAPs).

The generalized assignment problem (GAP) examines the minimum cost assignment of n jobs to m agents such that each job is assigned to exactly one agent subject to capacity restrictions on the agents. The generalized assignment problem is an NP-hard combinatorial optimization problem [12]. The formulation of this problem is:

$$(GAP) : \begin{cases} Max \sum_i \sum_j c_{lj} x_{lj} \\\\ \sum_j a_{lj} x_{lj} \le b_i \ \forall i \in I \\\\ \sum_i x_{ij} = 1 \ \forall j \in J \end{cases}$$

- $c_{ij}$ : the cost of assigning job $j$ to agent $I$;
- $a_{ij}$ : the capacity absorption when job $j$ is assigned to agent $i$;
- $b_i$ : the available capacity of agent $i$;
- $x$ : the assignment variable equals $1$ if agent $i$ is to perform job $j$, $0$ otherwise.

This table summarizes the correspondence between GAP and MCRPHR :

Table 1. Correspondence of the complexity between (GAP) and (MCRPHR)

| Problem : GAP | Problem : RPHRC |
|---|---|
| | fixed value $\quad k$ |
| Object $i$ | Agent Candidate $(i,j)$ |
| Job $j$ | Post in Department $E_k$ |
| Maximize the profile | Maximize the weight |
| $max \sum_i \sum_j p_{lj} x_{lj}$ | $Max \sum_{\substack{j=1 \\ j \ne k}}^{NU} \sum_{i=1}^{\tilde{N}_{jk}} \beta_{ji}^{k,\alpha_k} X_{ij}^k$ |
| | Capacity constraint |
| Resource constraint | $\sum_{\substack{j=1 \\ j \ne k}}^{US} \sum_{i=1}^{\tilde{N}_{jk}} X_{ij}^k \le C$ |
| $\sum_j a_{lj} x_{lj} \le b_i$ | $\sum_{\substack{j=1 \\ j \ne k}}^{NU} \sum_{i=1}^{\tilde{N}_{jk}} r_{jk}^{i,} X_{jk}^i \le R_k$ |
| Priority Constraint: | Priority Constraint: |
| $\sum_i x_{ij} = 1$ | $X_{lj}^k \left( \sum_{i=1}^{l} X_{ij}^k - l \right) = 0$ |
| | $\sum_{k=1}^{NE} X_{ij}^k \le 1$ |
| The displacements between the units of production   are dependents | |

We note that the reallocation problem can be decomposed into several inter-related sub reallocation problem $P_{k0}$ together by a variable $k$ and other constraint related to this variable such as the capacity constraint, positions Conservation of constraint and strain posts cost . A sub problem can be formulated as follow for $k = k_0$:

$$Max(F^a) = Max\left(Trace\left( \beta_{k0}^\alpha \ X_{k0}\right)\right)$$

Under the constraints:

$$(\boldsymbol{P_{k0}}): \begin{cases} Trace(\beta_{k0}^{\alpha} \, X_{k0}) \geq 0 \\[2em] X_{ji}^{k0}\left(\sum_{i=1}^{l} X_{ji}^{k0} - l\right) = 0, \quad \forall \, l \in \left[1, \widetilde{N}_{jk0}\right] \\[2em] \sum_{\substack{j=1 \\ j \neq k0}}^{NU} \sum_{i=1}^{\widetilde{N}_j} X_{ij}^{k0} \leq C_{k0}, \quad \forall \, i \in \left[1, \widetilde{N}_{jk0}\right] \ and \ \ \forall \, j \in [1, NU] \\[2em] \sum_{\substack{j=1 \\ j \neq k0}}^{NU} \sum_{i=1}^{\widetilde{N}_{jk0}} r_{ji}^{k0} \, X_{ji}^{k0} \leq R_{k0}, \forall \, i \in \left[1, \widetilde{N}_{jk0}\right] \ and \ \ \forall \, j \in [1, NU] \\[2em] \sum_{k=1}^{NU} X_{jk0}^{i} \leq 1, \ \forall \, i \in \left[1, \widetilde{N}_{jk0}\right] \ and \ \ \forall \, j \in [1, NU] \end{cases}$$

We notice that this formulation is similar to generalized assignment problem (GAP) known in the literature as a NP-hard problem [12]. For this, the complexity of the multi constraints reassignment problem can be evaluated and justified by the complexity of the (GAP).

For a given instance, our problem studied consist to search the optimal solutions allowing to maximize the objective function *F(X)* by using a metaheuristic algorithm such as the genetic algorithm.

## 4.  GENETIC ALGORITHM OF RESOLUTION

### 4.1.  Genetic algorithm

The method used for solving this problem is the genetic algorithms. It is part of the family of evolutionary algorithms. They have attracted the interest of many researchers starting with Holland [13], who developed the basic principles through Goldberg [14], which used to solve real problems of optimization. Other researchers have followed this path including Davis [15], Mahfoud [16], Michalewicz [17], etc …

In our approach, we used as a real encoding method of representation, the binary representation of sub-matrix, each sub matrix is composed by lines vectors that can be encoded by an array of Booleans: *0* or *1*. The applied methods in this approach are:
- Random generation of the initial population;
- Uniform Selection (US);
- Matrix Crossover (MOX);
- Matrix Mutation (MMP);
- Insertion Method (inserting elitism).

### 4.2.  Global algorithm

The global algorithm is composed of the following instructions:

**STEP 1**
Define the tolerance coefficient $\alpha$
Define the number of units $NU$
Define the candidate's number in each unit $E_j$
Define the precision
Constructing the global matrix: $\beta^{\alpha} = \{\beta_k{}^{\alpha} \; /1 \leq k \leq NS\}$

**STEP 2**
Generating the initial population composed of $N$ binary matrix assignment :
$$X = \{X_k \; /1 \leq k \leq NS\}$$

**STEP 3**
**Calculate** $F^{\alpha}(X) = \sum_{k=1}^{NS} \; \boldsymbol{Trace}\left(\beta_k^{\alpha_k} X_k\right)$ ***and* check** constraints,
**Arranging** the solutions in the list $N$

**STEP 4**
**Iteration=1**

 **Repeat**
    **Select** two solutions X1 and X2 from the list N
    **If** $\mathrm{Max}(F^{\alpha}(XC1), F^{\alpha}(XC2)) > \mathrm{Max}(F^{\alpha}(X1), F^{\alpha}(X2))$ ***and* check** constraints **Then**

       **Cross**  X1  and  X2 :
                  X1 ⟶ XC1 and X2 ⟶ XC2

       **If** $F^{\alpha}(XC1) > F^{\alpha}(XC2)$ **then**
                  **Mutate** $XC$, XC1 ⟶ XM
       **Else**
                  **Mutate** $XC2$, XC2 ⟶ XM
       **End if**

       **If** *F(XM) > Max(F(XC1),F(XC2))* ***and* XM verifies** the constraints **then**
                   **Insert** the solution in the list $N$
                   **Iteration=Iteration+1**
       **Else**
                    **Reject** *XM*
       **End if**
 **Until** $(F^{\alpha}(XM) - F^{\alpha}(X0))/F^{\alpha}(X0) < Precision$
**END**

## 5.    EXPERIMENT

### 5.1.  Description of the instance of the studied problem
        In this section, we present an example to valid this approach by using the genetic algorithm. For this, we consider an enterprise composed of three production units (*E1*, *E2* and *E3*). Our work approach is based on the following hypotheses:

- Each unit includes a number of agents wanting to change their original post of work by taking into account their choices.
- The data associated with individual weights of candidates are randomly generated in the interval [50, 100].
- The all posts are possessed the same cost value $r_{jk}^{i}$.
- The tolerance coefficients value is identical for each unit of production: $(\alpha_{k=1} = \alpha_{k=2} = \alpha_{k=3} = \alpha)$.

        The Table (2, 3 and 4) summarize the values of the individual's weight of candidates in each unit of production and for several of tolerance coefficient values α. Moreover, the Table 5 summarize the  constraint values $C_k$ and the average weight values $\overline{W}_0^k$.

Table 2. Change of post to the unit E1 (k=1)

| Original site | $\beta_{ij}$ ($\alpha$=0) | $\beta_{ij}$ ($\alpha$=1/4) | $\beta_{ij}$ ($\alpha$=1/3) | $\beta_{ij}$ ($\alpha$=1/2) | $\beta_{ij}$ ($\alpha$=2/3) | $\beta_{ij}$ ($\alpha$=3/4) | $\beta_{ij}$ ($\alpha$=1) |
|---|---|---|---|---|---|---|---|
| E2 | **97** | 76 | 70,67 | 60 | 49,33 | 44 | 28 |
| E2 | **75** | 67 | 61,67 | 51 | 40,33 | 35 | 19 |
| E2 | **69** | 43 | 37,67 | 27 | 16,33 | 11 | -5 |
| E2 | **67** | 43 | 37,67 | 27 | 16,33 | 11 | -5 |
| E2 | **64** | 29 | 23,67 | 13 | 2,33 | -3 | -19 |
| E2 | **57** | 22 | 16,67 | 6 | -4,67 | -10 | -26 |
| E2 | **54** | 20 | 14,67 | 4 | -6,67 | -12 | -28 |
| E2 | **51** | 16 | 10,67 | 0 | -10,67 | -16 | -32 |
| E2 | **50** | 13 | 7,67 | -3 | -13,67 | -19 | -35 |
| E3 | **96** | 80 | 74,67 | 64 | 53,33 | 48 | 32 |
| E3 | **50** | 39 | 35 | 26,5 | 18 | 13,75 | 1 |

Table 3. Change of post to the unit E2 (k=2)

| Original site | $\beta_{ij}$ ($\alpha$=0) | $\beta_{ij}$ ($\alpha$=1/4) | $\beta_{ij}$ ($\alpha$=1/3) | $\beta_{ij}$ ($\alpha$=1/2) | $\beta_{ij}$ ($\alpha$=2/3) | $\beta_{ij}$ ($\alpha$=3/4) | $\beta_{ij}$ ($\alpha$=1) |
|---|---|---|---|---|---|---|---|
| E1 | **90** | 83 | 79 | 70,5 | 62 | 57,75 | 45 |
| E1 | **89** | 78 | 74 | 65,5 | 57 | 52,75 | 40 |
| E1 | **83** | 76 | 72 | 63,5 | 55 | 50,75 | 38 |
| E1 | **82** | 69 | 65 | 56,5 | 48 | 43,75 | 31 |
| E1 | **77** | 58 | 54 | 45,5 | 37 | 32,75 | 20 |
| E1 | **63** | 21 | 17 | 8,5 | 0 | -4,25 | -17 |
| E1 | **62** | 9 | 5 | -3,5 | -12 | -16,3 | -29 |
| E3 | **66** | 86 | 82 | 73,5 | 65 | 60,75 | 48 |
| E3 | **54** | 74 | 70 | 61,5 | 53 | 48,75 | 36 |
| E3 | **51** | 60 | 56 | 47,5 | 39 | 34,75 | 22 |
| E3 | **51** | 35.25 | 53 | 44,5 | 36 | 31,75 | 19 |
| E3 | **50** | 39 | 35 | 26,5 | 18 | 13,75 | 1 |

Table 4. Change of post to the unit E3 (k=3)

| Original site | $\beta_{ij}$ ($\alpha$=0) | $\beta_{ij}$ ($\alpha$=1/4) | $\beta_{ij}$ ($\alpha$=1/3) | $\beta_{ij}$ ($\alpha$=1/2) | $\beta_{ij}$ ($\alpha$=2/3) | $\beta_{ij}$ ($\alpha$=3/4) | $\beta_{ij}$ ($\alpha$=1) |
|---|---|---|---|---|---|---|---|
| E1 | **90** | 83 | 79 | 70,5 | 62 | 57,75 | 45 |
| E1 | **89** | 78 | 74 | 65,5 | 57 | 52,75 | 40 |
| E1 | **83** | 76 | 72 | 63,5 | 55 | 50,75 | 38 |
| E2 | **82** | 69 | 65 | 56,5 | 48 | 43,75 | 31 |
| E2 | **77** | 58 | 54 | 45,5 | 37 | 32,75 | 20 |
| E2 | **63** | 21 | 17 | 8,5 | 0 | -4,25 | -17 |

Table 5. The example of average  weight and capacity constraint values

| Average  weight $\overline{W}_0^k$ | 96,2 | 79,72 | 114,71 |
|---|---|---|---|
| Capacity constraint $C_k$ | 90 | 83 | 79 |

## 5.2.  Results and discussion

The following table summarizes the main results of our test. They were obtained on a computer having CPU *Pentium i5 2.5GHz* with *4GB* of *RAM*. The genetic algorithm used was encoded by the *C++* language.

For better interpretation, the obtained numerical results are graphically visualized in the next figures. On the primary experience, we interest to show the influence of number of candidates on the generation time and convergence time. In order to do this, we take three instances composed consecutively of *29*, *58* and *116 candidates*. In this test, the genetic algorithm is started with *40* individuals considered as the initial population size, and *50* iterations as the stopping condition applied [1]. These two parameters were experimentally justified by the figures analysis.

Other results are presented, they concern the study of the time consumed to generate the initial populations for different sizes according on number of candidates wishing to change their positions and these results are illustrated in the Figure 1. By regarding this figure, we can observe that the generation time is increased with the effective of candidates. In addition, if we elevate the number of candidates by a portion *2* or *3*, the generation time can also be assessed by the same portion.
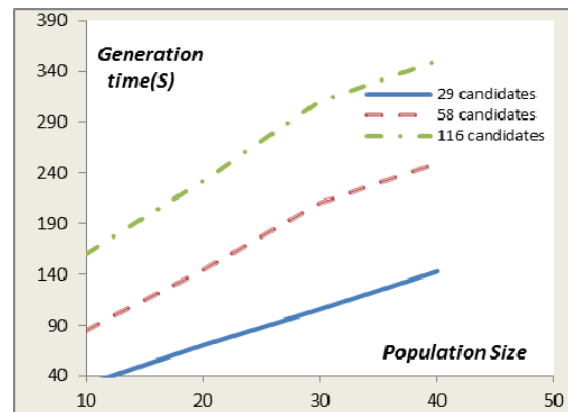
Figure 1. Generation time depending on number of individuals

The main goal of this research is to carry out investigation of the influence of one of the key GA parameters – population size (number of chromosomes) – on the algorithm performance for identification of an optimal matrix of reassignment of candidates.

On Figure 2, the precision issue the fitness function values, obtained during the *60* iterations by using a different population size: *10, 20,30* and *40* are shown. Each test consists to determine the good population size to lead to the best solution.
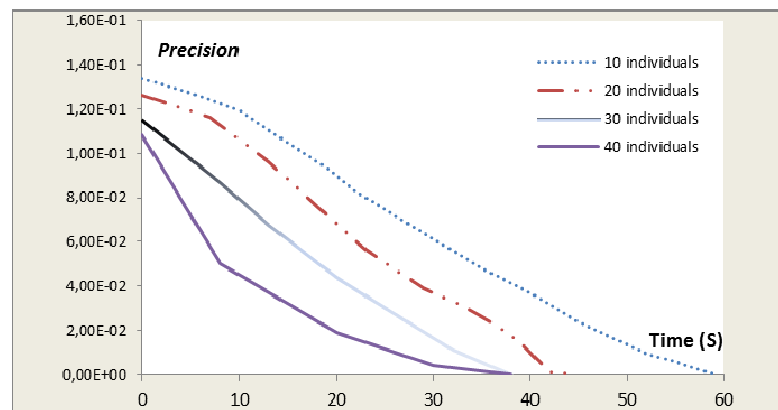


Figure 2. Precision factor depending on execution Time (Without Generation time) for an instance composed of 29 candidates

The precision factor calculated by this expression: $P = \dfrac{F(Sopt) - F(S0)}{F(Sopt)}$

Where *Sopt* is the average solution optimal obtained for *10* tests and *S0* is the best solution issue from the initial population. The graphical results show that the GA could not find accurate solution using small population size under *20* chromosomes. That needs at least *30* chromosomes in population for achieving a better solution of the generation time according to the number of genetic population. We can also conclude that the probability to obtain a precision factor approximately equal to *0*.

On Figure 3, the fitness function values, obtained during the *60* algorithm runs for *40* individual are shown. It can be observed in this figure that the improvement of the fitness function (*F*) is rapid and becomes slower until the stagnation of this function. This stagnation is to show the convergence of the objective function to an optimal value *Wopt=1061.7* for $\alpha = \frac{1}{4}$. The optimal solution *X* obtained corresponds to global weighted matrix $\beta^{\alpha}$ that is presented as follow:

$$\beta^\alpha = \begin{pmatrix} \beta^\alpha 1 \\ \beta^\alpha 2 \\ \beta^\alpha 3 \end{pmatrix} \text{ and } X = \begin{pmatrix} X1 \\ X2 \\ X3 \end{pmatrix}$$

With :

$$X1 = \begin{pmatrix} 1\ 1\ 1\ 1\ 0\ 0\ 0\ 0 \\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0 \end{pmatrix}$$
$$X2 = \begin{pmatrix} 1\ 1\ 1\ 1\ 0\ 0\ 0 \\ 1\ 1\ 0\ 0\ 0\ 0\ 0 \end{pmatrix}$$
$$X3 = \begin{pmatrix} 1\ 1\ 0 \\ 1\ 1\ 0 \end{pmatrix}$$

The value *1* indicates that the employee is reassigned, however the value *0* indicates that the employee is not reassigned.
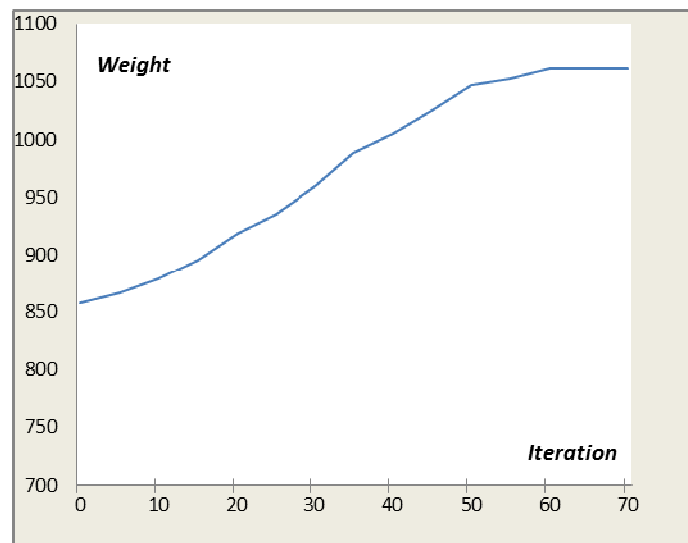


Figure 3. Variation of fitness function depending on number of iterations an instance composed of 29 candidates ($\alpha = \frac{1}{4}$)

The algorithm described above has various parameters, including the influential values strongly on its quality. Indeed, we conducted an empirical study of the adjustment of these parameters to obtain good results of performance. In this approach, we have integrated the operator uniform matrix crossover and mutation matrix (matrix HPRM) [3],[10]. These two operators are operated alternately following a so-called "Flip-Flop crossover-mutation." [3]. This implies that the mutation operator is able to be reached only in the case when the solution obtained by the crossing procedure does not satisfy all the constraints. In addition, the choice of stopping criterion based on the stabilization of the fitness function strengthens the convergence of this approach towards good solution. These new procedures also allow reduce the computation time and improves solution the solution [3].

In order to better judge the validity of our approach, we make a comparison between our approach and genetic approach used to solve the first work "A Meta-heuristically Approach of the Spatial Assignment Problem of Human Resources in Multi-sites Enterprise" [1] according to genetic operators and the stop condition. In this work we applied the maximum number of iterations as a stopping criterion which we predefined in the onset running. However, this criterion is insufficient to falling into the best solution. In addition, the application of classical crossover and mutation operators in the work [1] serves only serves to provide a solution in more time and lower quality compared to the solution obtained by our approach described in this paper.

Through a synthesis of the literature on human resource allocation problems, there is no instance targeted to numerically compare the results associated of these problems with the results obtained by our approach. Indeed, we are interested to focus on the work in treating certain term constrained assignment problem solving by genetic algorithms. The common point focuses on the use of conventional stop criteria

based on the number of maximum iterations and secondly on the application of crossovers and mutation operators adapted and reconstructed for the problem studied, we cite for example I.Younas [18], J.Park [19] .Xilin [20], and El Moudani [21].

Table 6 shows the results corresponding to number of displacements according to $\alpha$. We see that this number can be reduced to *14* candidates when this coefficient is increased to *1/3* given that *18* assigned candidates has engendered a global weight *1435* and *14* assigned candidates has engendered a global weight *948.91*. In addition, these movements become not possible where $\alpha \geq 0.5$, this is can be explained by dissatisfied of objective constraint.

Table 6. Induced weight and number of possible displacement depending on tolerance factor

| Tolerance coefficient | Number of possible replacement | $Trace(\beta^{k,\alpha}X^k)$ |
|---|---|---|
| α=0 | 18 | 1435 |
| α=1/4 | 16 | 1061.7 |
| α=1/3 | 14 | 948.91 |
| α>=1/2 | **All displacements are interdict** | |

Table 7 shows the variation between $\Delta W_k$ (global weight) engendered by the personnel reassignment depending on tolerance coefficient $\alpha$. The numerical experiments show that increasing the gap $\Delta W_k$ that can be considerably as an improvement the resulting value of the objective function (average results). The results show that variation of global weight or profile $\Delta W_k$ is decreasing with $\alpha$ However, the best parameters of α are $\alpha = \frac{1}{4}$ and $\alpha = \frac{1}{3}$ witch conduct to improvement or equilibrium of the global weight variation ($\Delta W_k \geq 0$) for each unit of production $E_k$.

Table 7. The improvement weight by the reassignment process for each unit ek depending on tolerance coefficient

| Value of α | Site | E1 (k=1) | E2 ( k=2) | E3 ( k=3) |
|---|---|---|---|---|
| | $\overline{W}_k^0$ | 74 | 71 | 72 |
| | $W_k^+$ | 569 | 541 | 351 |
| α=0 | $W_k^-$ | 550 | 488 | 288 |
| | $\Delta W_k$ | 19 | 53 | 63 |
| | $\Delta \overline{W}_k$ | 2,17 | 4,61 | 3,50 |
| | $\overline{W}_k$ | 26 | 22,72 | 18,26 |
| | $W_k^+$ | 495 | 464 | 351 |
| α=1/4 | $W_k^-$ | 473 | 424 | 288 |
| | $\Delta W_k$ | 12 | 40 | 63 |
| | $\Delta \overline{W}_k$ | 1,38 | 2,50 | 3,94 |
| | $\overline{W}_k$ | 25,89 | 24,59 | 23,73 |
| | $W_k^+$ | 418 | 382 | 351 |
| α=1/3 | $W_k^-$ | 411 | 357 | 288 |
| | $\Delta W_k$ | 7 | 25 | 63 |
| | $\Delta \overline{W}_k$ | 0.7 | 2.08 | 9 |
| | $\overline{W}_k^0$ | 29,38 | 21,92 | 18,91 |
| α=1/2 | Objective constraint is not satisfied | | | |

In order to study the problem of personnel reassignment by using this genetic algorithm. We used *30* individuals as population size and *50* iterations as stopping condition. We have show that the solution obtained in the reasonable time can be improved the productivity or maintain it to equilibrium productivity for each unit $E_k$. The parameter $\alpha$ must be verified the following condition: $\alpha < W_{moy}^k / \overline{W}_0^k$ for starting our genetic algorithm in good conditions to obtain the best solution.

## 6. CONCLUSION

We presented in this paper an optimizing approach for multi constraints assignment personnel problem. This approach allow ensuring the optimal repartition of human resources to achieve the desired objective fixed by managers. We showed that this problem is very complex and it is similar proximately to Generalized Assignment Problem. For this, we used a genetic algorithm to solve this problem by the good choice of parameters genetic and tolerance coefficient. The optimal solution obtained in the reasonable time ensures at less improvement the productivity or at less conduct to equilibrium of average productivity for each unit of production. The optimal solution obtained allows validating the proposed approach.

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