An Improved Resolution for a Constrained Recruitment Problem using Genetic Immigration Approach

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Abstract— In this paper, we propose a new genetic approach to improve the solution of a constrained recruitment problem of humun resources. This problem is an extension of a Multiple Knapsack Approach for Assignment Problem of Human Resources that is a NP-hard combinatorial problem. In the previous work [1], we have formulated this problem and solved it using the last proposed genetic algorithm for obtaining the optimal assignment of qualified employees that ensures the maximization the specific profits, but we have noticed that the phenomenon of stagnation of this algorithm persists although increases in the number of iterations lead to a significant consumption of computing time and memory space. To remedy this problem, we propose in this paper to integrate new genetic methods, such as Standard Immigration Genetic (SIG) [2], able of improving the convergence towards the optimum. This process is based on the insertion of a percentage of best individuals from previous generations in the genetic population to improve the diversity of the population and to bias the search direction for obtaining the best solution. The results are being evaluated and compared with other results obtained using the last proposed genetic approach.

Keyword— Constrained Recruitment, Multiple Knapsack, Improvement, Genetic Algorithm, Immigration Approach

1 Introduction

Human resources are considered as one of the most important sources of today's enterprise. Human resources management is more important than other competitive sources since these people use other assets in organization, create competitiveness and realize objectives [5][6]. The recruitment is a decisive step in the human resources policy, as it can have an effect contrary to the aims pursued. It is appropriate, therefore, to define clearly the policy to be followed and the means by which to support her.

When the recruitment is managed under various constraints, it this can be modeling as the classical assignment problems to assign m agents to m posts, where each couple (post, agent) has a cost genetically, this problem is an extension of our work that we carried out as mobility of human resources under constraints, and more precisely the recruitment problem that we formulated by an approach based Multiple Knapsack Problem (MKP) that is a NP-hard combinatorial problem [1] [2].

Our objective of the standard assignment problem is to maximize the summation of the weights of the employees, their individuals weights are measured during interviews by collection of information on employees to be recruited by transferring and diversifying their competencies and qualifications. However, the bad selection of these employees can influence negatively within multiple services in enterprise [7][11]. Nowadays, a non-optimized selection of candidates to recruit can lead to a lack of motivation, and can influence the work team and consequently the performance of a production site.

In the previous work, we have proposed an genetic approach to search an optimal solution, but we have noticed that the phenomenon of stagnation of this algorithm persists although increases in the number of iterations lead to a significant consumption of computing time and memory space

To solve our problem do this, we implement genetic algorithms; the resulting solution allows us to determine the optimal allocation of employees to posts locating in different units of production in the enterprise to maximize the productivity

The rest of this paper that is which complements our work addressing the problem of mobility of human resources under constraints [1][2] is organized as follows: Firstly we will present a global formalism of our recruitment problem that it have been solved by using the proposed genetic approach detailed in work 2. Secondly, we will present the random immigration SIG approach will be used [3] to improve the solution. In Section 3, computational experiments were performed through the same instance of problem exploited in work 2. The comparison with the results obtained the numerical result with last proposed genetic approach and with SIG random immigration genetic shows the performance to introducing of SIG for assignment problem of human resources for improving the solution and therefore can make an important contribution to improving the profits of recruitment productivity within the unity of production.

2 Formulation of the Problem and Last Solving Method

2.1 Formulation of problem

Based on the correspondence established between the recruitment problem and that multiple knapsack, we can deduce the formulation of the constrained recruitment problem [4].

The recruitment approach in this section is based on a model of multiple knapsacks. So, after the rapprochement between our problem and a of Multiple Knapsack problem, a dimension of a knapsack corresponds to a production site or service, and profiles of an object to put in a dimension of knapsack corresponds to individual weight of a employee to recruit. The goal of this approach is to recruit and assign the qualified employees to production sites to maximize the overall profile of the enterprise under the constraint of the budgetary costs and the capacity constraint.

Based the correspondence established between the recruitment problem and Multiple Knapsack problem, we have formulated our problem as follow:

$$\begin{cases} Max\ F = max \sum_{j=1}^{NS} \sum_{i=1}^{\tilde{N}_j} W_{ij} X_{ij} & (1) \\ \sum_{\substack{j=1 \\ j \neq k}}^{NS} \sum_{i=1}^{\tilde{N}_j} c_{ij}\, x_{ij} \leq C_j\ \forall j\ \in [1, NS] & (2) \\ \sum_{j=1}^{NS} X_{ij} \leq 1\ \forall i \in [1, \tilde{N}_j] & (3) \end{cases}$$

$\mathbf{X_{ij}}$ is the decision variable given by:

$$X_{ij} = \begin{cases} 1, \text{if the employee } i \text{ of class } j \text{ is assigned} \\ 0, otherwise \end{cases} \quad (4)$$

- (1) is the objective function;
- (2) is the constraint costs ;
- (3) is a constraint explains that a employee can't have two posts simultaneously in U_{ij}
- $U = \{\{U_j\} / j \in [1, NS]\}$ is set of production sites;
- $I = \{1, 2, \ldots, i \ldots, nc\}$:set of employees or employees;
- .W(i): Wight of employee i with $W(i) > W(i+1), \forall i \in I$;
- $\tilde{N}_j$ is number of employees desiring to occupy the posts in production unit U_j;
- N_j is the number of employees assigned to U_j ;
- n_j is the number of vacant posts in U_j ;
- C_j is the cost of all posts in U_j
- Cost ist global matrix cost of post, it explains that the sum of the budgetary costs posts that will be occupied by employees assigned (recruited) should not exceed the aggregate cost fixed by the manager.

Based on the complexity of the Multiple Knapsack problem known as an NP Hard problem, we can see that the assignment problem is also a NP Hard problem. An optimal solution to problem [12] can be obtained by a suitable resolution method Generally, the resolution of instances is done through genetic algorithm include a heuristics seen to be effective in providing good solutions [13][15].

2.2 Last Solving Approach

The last solving approach is based on a genetic algorithm which is a one of the family of evolutionary algorithms and is computerized search and optimization algorithms based on the mechanics of natural genetics and natural selection [5]. In Genetic Algorithm, a population of potential solutions termed as chromosomes are evolved over successive generations using a set of genetic operator's selection, crossover and mutation.

First of all, based on some criteria, every chromosome is assigned a fitness value and then the selection operator is applied to choose relatively fit chromosomes to be part of the reproduction process. In reproduction process new individuals are created through application of operators. Large number of operators has been developed for improving the performance of GA, because the performance of algorithm depends on the ability of these operators [8][9]. The mutation and crossover operator is used to maintain adequate diversity in the population of chromosomes and avoid premature convergence.

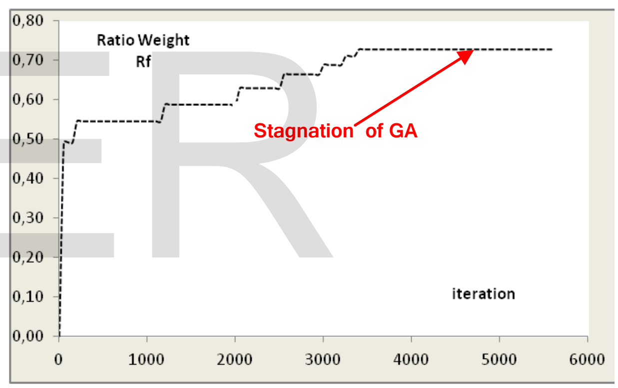

Fig. 1. Optimum solution according to number of iterations using the last proposed genetic approach

So, when we have obtained the optimal solution by this proposed genetic approach, we have noticed that the phenomenon of stagnation of this algorithm persists although increases in the number of iterations lead to a significant consumption of computing time and memory space. To remedy this problem, we propose in this paper to integrate new genetic methods, such as Standard Immigration Genetic (SIG) [2].

3 Genetic Immigration algorithm to Improve The Solution (SIG)

The crossover and mutation method is essentials component of evolutionary algorithms, playing an important role especially in solving hard optimization problem[9] .The immigration is based on structured immigration which consists in benefiting individuals not inserted during the previous generations (resulting from the crossover and mutation operators of the selected individuals). Thus, a percentage of the most powerful individuals will immigrate after an interval of time instead of the same number of the lowest individuals in the last generation. The complexity of immigration is decreased by executing it only every several generations [3].

where random immigrants replace worst individuals in the population, pc is the crossover probability, and pm is the mutation probability. Random Immigration" where the randomly created individuals are inserted into the population every generation by replacing the worst individuals or some individuals randomly selected The pseudo-code for the standard GA with random immigrants investigated in this paper, denoted SIG, is also shown in Figure. 2, where random immigrants replace worst individuals in the population, pc is the crossover probability

```
Begin
Initialize population P randomly with constraints validation;
Evaluate population P;
for(iitr=1; iitr<=iter; iitr++)
    Sel:=Select For Reproduction (P)          // N individuals
    CX := Crossover (Sel, Px)        // Px is the crossover probability
    Mut := Mutate (CX, Pm)                    //Pm is the mutation probability
    Evaluate new individuals Mut     // EvaluteMut and sort in descendant
      P' = Elitisme(Mut(1; N/2))     // Perform elitism
    ImPop = (Mut(N/2; N))
    if  mod( iitr, Itinsert ) == 0 then   // Execution of SMIGA
       evaluate immigrants subpopulation ImPop
        replace the n worst individuals in P
    Endif
```

Fig 2 Random Standard Immigration Genetic (SIG)

STEP 1

Define the Class of employee

Construct the sites NS $U = \{\{U_j\} / j \in [1, NS]\}$

Construct the Weight Matrix of candidates MW $/ \mathrm{W(i)} > W(\mathrm{i}+1), \forall \mathrm{i} \in \mathrm{I}$;

Construct the Costs Matrix C_{ij} *, Global Costs Vector* C_j

STEP 2

Generate the initial solution of recruitment population $X = \{X_{ij} / i \in [1, \widetilde{N}_j], \forall j \in [1, NS]\}$

STEP 3

Calculate $F = max \sum_{j=1}^{NS} \sum_{i=1}^{\widetilde{N}_j} W_{ij} X_{ij}$ *and check constraints,*

STEP 4

k= 1 ***Repeat*** // Starting

Select two solutions X1 and X2 from the list N

If $Max(F(XC1^k), F(XC2^k)) > Max(F(X1^k), F(X2^k))$ *and check constraints*

Then *Cross* $(X1^k, X2^k)$ // Crossover of $XC1^k$ and $XC2^k$

$X1^k \longrightarrow XC1^k$,
$X2^k \quad\quad XC2^k$

If $F^\alpha(XC1^k) > F^\alpha(XC2^k)$ ***then***

Mutate $(XC1^k)$: $XC1^k \longrightarrow XM^k$ // Mutation of XC1

Else

Mutate $(XC2^k)$: : $XC2^k \longrightarrow XM^k$ // Mutation of XC2

End if

Insert the solution in list N // insertion in population list

```
 If          F(XM^k) > Max(F(XC1^k),F(XC2^k)) and XM^k check  Constraints then
Else              Reject XM^k                                   // Reject solution

// introducing the pseudo code of sig algorithm

 If  k=k/10        // iteration processes of SIG
     itInser=k

  Evaluate population P;
For (iitr=1; iitr<=iter; iitr++)
     Sel:=Select For Reproduction (P)              // N individuals
     XC^k := Crossover (Sel, Px)                    // Px is the crossover probability
     XM^k := Mutate (XC^k, Pm)                      //Pm is the mutation probability
     Evaluate new individuals Mutate                // EvaluteMut and sort in descendant
      P' = Elitisme(Mutate(1; N/2))                  // Perform elitism
     ImPop = (Mutate(N/2; N))
     If  mod( iitr, Itinsert ) == 0 then             // Execution of SMIGA
         Evaluate immigrant's subpopulation ImPop
         Replace the n worst individuals in P
     Endif
Endfor
End if
           Until F(XM^k) − F(X0))/F(X0) < Precision
END
```

Fig 3 the new approach genetic integrating the SIG to resolve the recruitment problem

4 Results And Discussion

To evaluate the performance of the new proposed genetic approach for improving the solution of constrained recruitment Problem of Human Resources. To do this, we first exploited the same instance of previous work [2] (4 units and 60 candidates). In addition we have run a machine Pentium i5 2.5 GHz with 4GB of RAM, the proposed SIG algorithm including the SIG, the SIG algorithm is re-executed on a ten times and the average of these 10 values is taken for interpretation. The parameters Pc and Pm are varying with the generations and the inverse of the length row of assignment matrix, and a fixed number of generations of 80 individuals.

Comparison of solution quality and the convergence time:
Results for last proposed genetic algorithm (LPGA) and the SIG algorithm are shown in Figures 5 and 6. Its represents the results of the best averages of the ratio weight $Rf = \frac{F-F0}{F0}$ for SIG and LPGA according of the number of iterations. F0 represent the best fitness value where number of iteration=0 or before the start of the genetic algorithm.

For the LPGA algorithm, the objective function is stabilized in the best ratio weight is stabilized at Rf=0.65 or at best weight can be engendered be by the recruitment of candidates:

$F(LPGA) = 1.65 * F0$ during 3500 iterations with the stagnation phenomena is persist, or. However, the SIG algorithm is

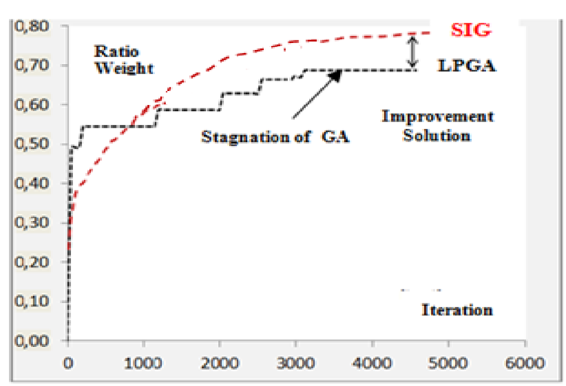

Fig. 4. Comparison of the computation time to find the optimum solution for SIG and LPGA

converged to best ratio weight $Rf = 0.8$ or or the best weight can be engendered be by the recruitment of candidates: $F(SIG) = 1.80 * F0$ only during 3200 iterations. So, the ratio of improvement can be calculated by $Imp = F(SIG) - F(LPGA) = 0.15 * F0$.

To compare these results, then we can see that a SIG methods serves to improve the optimal value of function fitness obtained initially by LPGA causing a stagnation phenomena of LPGA. This process can be explain by the insertion of a percentage of best individuals from previous generations in the genetic population to improve the diversity of the population and to bias the search direction for obtaining the best solution.

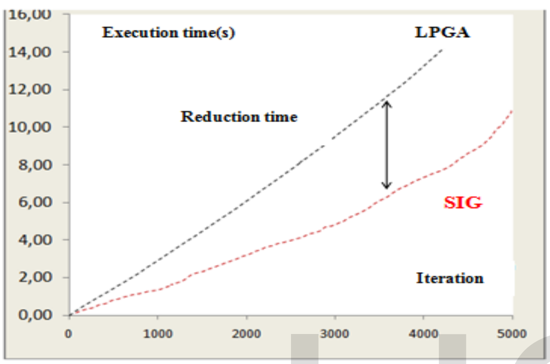

Fig. 5. Comparison of the computation time to find the optimum solution for GIS and LPGA

In the other hand, the best solution of recruitment obtained by LPGA and SIG corresponding respectively to Rf=0.65 Rf=0.80 represent the good repartition candidates recruited able for maximize the global profits.

$$S(LPGA) = \begin{pmatrix} 1\,1\,1\,\mathbf{1}\,0\,0 \\ 1\,0\,0\,0\,0\,0 \\ 1\,1\,0\,0\,0\,0 \\ 1\,1\,1\,1\,0\,0 \end{pmatrix}, S(SIG) = \begin{pmatrix} 1\,1\,1\,\mathbf{0}\,0\,0 \\ 1\,\mathbf{1}\,0\,0\,0\,0 \\ 1\,1\,\mathbf{1}\,0\,0\,0 \\ 1\,1\,0\,0\,0\,0 \end{pmatrix}$$

The comparison between these two solutions of recruitment, lead us to conclude that the new resolution approach SIG can also help us to place the best element in the best assignment position in order to well maximize the overall profits of enterprises.

5 Conclusion

In this paper, we have proposed a new genetic approach to improve the solution and to remedy the stagnation of function fitness for a constrained recruitment problem of human resources based on Multiple Knapsack problem which is a NP-hard problem. The experimental result showed the performance of the approach SIG to as Standard Immigration Genetic (SIG) , able of improving the convergence towards the optimum to obtain the best recruitment matrix serves to place the right employees in the right post in order to maximize he profitability and the productivity within the enterprise.

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