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Genetic algorithm with immigration strategy to solve the fixed charge transportation problem

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ABSTRACT

This paper is about improving the performance of genetic algorithm (GA) to solve the fixed-charge transportation problem (FCTP). Several approaches have been developed, based on adaptation and improvement of genetic operators. We propose a new genetic algorithm adopting an immigration strategy to maintain the diversity in the population and then overcome the stagnation of the values of the objective function. Thereby, we applied two types of immigration, random immigration and memory-based immigration. The numerical results obtained with several standard instances of the FCTP problem demonstrate the effectiveness of these strategies in improving the performance of the GA. Especilly, for the second strategy.

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1. INTRODUCTION

The fixed charge transportation problem (FCTP) is a complex combinatorial optimization problem of great importance that has attracted high interest from several researchers to achieve the optimal solution [1]. FCTP is classified as a complex problem that is difficult to solve by classical methods [2], due to the fixed costs, as well as the computational time required an exponential time to find solution. Therefore, metaheuristics can be used.

Genetic algorithms (GAs) including meta-heuristic approaches, developed by Jean Holland, have been employed extensively to solve the FCTP problem and other combinatorial problems. It is inspired from biological mechanisms. It consists of iterative processe which converge on the optimal solution [3], [4]. To benefit from the advantages of GAs as fundamental approaches and to improve its performance; in particular, to overcome the stagnation in certain values of the fitness function during a significant number of iterations during the genetic process, we proposed a new genetic algorithm based on immigration strategy [5]-[7].

In this paper, we present two immigration strategies for the genetic algorithm, random immigration and memory-based immigration, consisting of two distinct genetic algorithms. To demonstrate the impact of immigration strategy on the GA, we consider several instances of the considered problem, which are common academic problems. The numerical results obtained with immigration strategy show that, not only diversity can be maintained, but also, performances of genetic algorithm can be improved for the FCTP problem.

The rest of the paper is organized as follows: In the section 2, we present the description of the FCTP problem and its mathematical formulation. We provide brief discussions of works that address the FCTP problem by standard genetic algorithms in section 3. Then, in section 4, we propose two new genetic algorithms based on two immigration strategies. The first is called genetic algorithm with random immigration and the second is called genetic algorithm with structured memory-based immigration. In section 5, we present some numerical results to compare them with those already found by the sdandard genetic algorithm. The results presented concerning six well-known instances of the FCTP problem already cited in previous research. Finally, a conclusion presents an assessment of our work and our results.

2. PROBLEM DESCRIPTION

The FCTP is a case of the transport problem where an additional fixed cost is paid to send a stream from an origin to a destination. We have a group of sources $i = 1, ..., m$ with limited capacities S_i which provide several destinations $j = 1, ..., n$ which also require specific quantities of product D_j. A variable transportation cost is charged for each product unit sent by the producers to the warehouses plus a fixed cost regardless of the quantity transported. The problem seeks to find the quantity of product to send from each source to the destination to minimize the total fixed and variable transport costs. While the fixed cost makes the problem difficult to solve by conventional algorithms. It is better to consider the balanced problem, i.e., the availability equals the demands ($S_i = D_j$). Indeed, it is easy to find a solution for this type of problems.

The mathematical formulation of the FCTP is as follows:

$$Min\ Z = \sum_{i=1}^{m}\sum_{j=1}^{n}(c_{ij}\,x_{ij} + f_{ij}y_{ij})$$

$$y_{ij} = \begin{cases} 1, & if \quad x_{ij} > 0 \\ 0, & if \quad x_{ij} = 0 \end{cases}$$

$$s.t$$

$$\sum_{j=1}^{n} x_{ij} \leq S_i \qquad i = 1,2,\ldots,m$$

$$\sum_{i=1}^{m} x_{ij} \geq D_j \qquad j = 1,2,\ldots,n$$

$$x_{ij} \geq 0$$

c_{ij}: variable cost from centre i to point j;
x_{ij}: quantity send from centre i to point j;
f_{ij}: fixed cost from centre i to point j;
y_{ij}: a binary variable that takes 0 or 1;
S_i: quantity available in center i;
D_j: quantity requested by point j.

3. STANDARD GENETIC ALGORITHM METHOD

Genetic algorithms are among the evolutionary stochastic methods. They are proposed by Jhon Holland [4]. They are inspired from the natural biological mechanisms of the theory of evolution, proposed by Charles Darwin [8]. GAs are more used to solve complex optimization problems [8], [9].

3.1. Representation method

The way to represent the solution for a given problem is a crucial process in applying GA. Indeed, there are several representation methods adapted to the FCTP problem; among these methods, we find the matrix representation [10], [11], where each chromosome is represented using a matrix of size m×n with m+n -l positive elements. The matrix representation is not suitable for the FCTP, because they forced to fill several boxes with zero values. Furthermore, The FCTP problem is a network problem. In addition, the prüfer number encoding that can be used to solve different network problems. This representation is introduced by Mitsuo and Li [12].

We find also the priority-based representation, which is a new encoding for transportation problems. It was first used to solve the two-stage transport problem and it is adapted to the FCTP problem as well. In this encoding, each chromosome is encoded by an integer string, and its length is equal to the sum of number of sources and number of destination. The value and the position of gene allow to identify the priority of the node which help to the construction of a transport tree. This encoding facilitates the adaptation of the genetic algorithm for the FCTP problem [13]. An example of a representation of an individual is presented in Figure 1. It should be noted that for each type of representation, different genetic operators must be adapted. In the rest of the paper, we are mainly interested in the priority based representation.

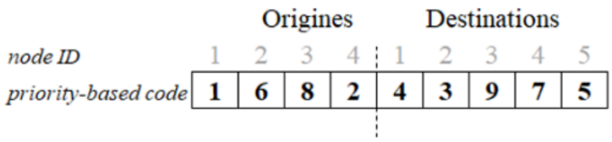

Figure 1. Example of the cromosome by priority based-representation

3.2. Initialisation

Generally, the GA has five basic components. At the beginning, a set of possible solutions representing a population P(t), is initialized. In general, the initialization is done randomly or by other means depending on the objective and the programming strategy. For the generation t the individual represents a potential solution to the problem [14].

3.3. Crossover operator

Crossover operator is a process used in genetic algorithms to guide the algorithm to find a solution to a given problem. For the FCTP problem, several operators are applied to solve the problem by GA. We find the crossover operators OPEX, IPX, OX, PX [15], [16]. In this paper, we use IPX operator according to their performance and advantages. The progression of the IPX operator is depicted in Figure 2.

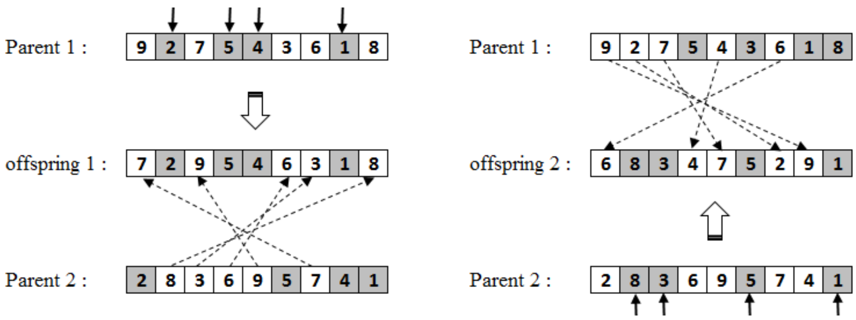

Figure 2. Example of the IPX crossover

3.4. Mutation operator

The mutation operator consists in exchanging positions within the same chromosome based on a some suitable probability. However, instead of using this operator, such as crossover operator, between two parents, we use it between two segments of a single parent. The importance of mutation appears in the solution quality. Different mutation operators are developed for different problem and with different type of encoding. For the FCTP problem, with the priority based encoding, it exists the mutation operators SWAP, inversion mutation, OPEX [17]. We are interested in the SWAP operator considers to be the most suitable mutation operator for our FCTP problem. The SWAP procedure illustrated in Figure 3.

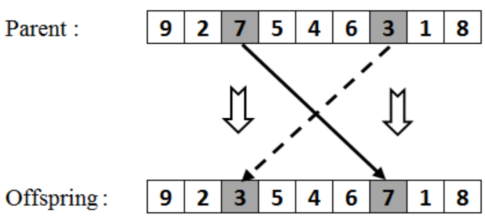

Figure 3. Example of the SWAP mutation

3.5. Evaluation and selection

Evaluation and selection are fundamental genetic processes. The first is a genetic process to calculate the objective function. It is linked to the representation method. It allows us to measure a solution and compare it to others in order to select the best ones. Thus, evaluation as shown in Figure 4 ensures that the best performing individuals will be retained after several iterations of the GA [18], [19].

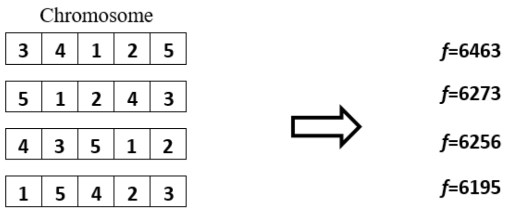

Figure 4. Example evaluation process

Selection process consists of choosing the individuals that have passed to the next generation of the GA. It ensures that the best individuals from the current population that still persist. The strong ones that survive have a higher probability of being selected to mate or mutate. Selection is an important process in genetic algorithms [20]. There are several selection schemes, namely selection by tournaments, selection by elitist, selection by linear ranks. The description of the selection method is based on the fitness distribution of the population before and after selection as introduced [21], [22].

4. THE PROPOSED METHOD

Usually, after a number of iterations, the standard genetic algorithm finds the best solution belonging to the current population. Nevertheless, to overcome stagnation and avoid convergence towards local optima; the immigration strategy is used which will introduce a diversity of the population and give more dynamism to explore and exploit new probable solutions. In our study, we use two main immigration strategies in order to obtain a better optimal solution compared to that obtained by the standard genetic algorithm. These strategies are presented:

4.1. Genetic algorithm with random immigration (RIGA)

The first strategy called "Random immigration" where randomly created individuals are inserted into the population in each generation by replacing a random number of individuals or the weakest individuals in the population. The random immigration procedure increases diversity in the population by substituting individuals from the current population for new individuals generated at random at each generation or after a number of generations [23]. In order to prevent random immigrants from disturbing the progress of ongoing research during the period when the environment does not change, the ratio r_i of the number of random immigrants with the population size n is usually set to a small value. Figure 5 presents the pseudo-code of GA with the random immigration strategy.

```
Begin
Initialize the population P randomly
Population evaluation P
For (iitr = 1; iitr <= iter; iitr ++)
        Sel: = Select for reproduction (P)
        IPX:=Crossover(Sel,Px) // Px is the probability of crossover
        SWAP:= Mutation(IPX, Pm) // Pm is the probability of mutation
        P' = Elitism(Mutation (1;N/2)) // elitism process
          If mod(iitr, ItInser) == 0 then // ItInser is the number of iterations before immigration
                Generate n random immigrants
                Evaluation of random immigrants
                Replace the worst individuals in P
        End if
End For
End
```

Figure 5. Pseudocode for the random immigration genetic algorithm–RIGA

4.2. Genetic algorithm with structured memory-based immigration

In the genetic algorithm with structured memory-based immigration (MIGA), the immigrants are not random. The considered technique involves structured memory immigration, which aims to take into account individuals who were previously excluded in the past generations. Instead of selecting the same number of individuals with the lowest capabilities from the most recent generation, a portion of the most powerful individuals will immigrate after a set amount of time. To simplify the process, immigration only occurs every few generations. Thus, after a defined interval of time, this procedure gives the chance to the best individuals to immigrate to the new population [24], [25]. This stategy has prove its performance for different problems. In fact, it gives a dynamism for the population to avoid stagnation in a set of solutions found. As a result, this method greatly improves genetic algorithms to obtain a best solution [26], [27]. The MIGA algorithm for the FCTP problem is described in Figure 6.

```
Begin
Initialize the population P randomly with constraints validation
Evaluate population P
For (iitr = 1; iitr <= iter; iitr ++)
        Sel: = Select for reproduction (P)
        IPX:=Crossover(Sel,Px) // Px is the probability of crossing
        SWAP:= Mutation(IPX, Pm) // Pm is the probability of mutation
        Evaluate new individuals SWAP // Evaluate mutation and sort in descendant
        P' = Elitism(Mutation (1;N/2)) // elitism process
          If mod(iitr, ItInser) == 0 then // Execution of MIGA
                Generate n memory immigrants & Evaluation of memory immigrants
                Replace the worst individuals in P
        End if
End For
End
```

Figure 6. Pseudocode for the genetic algorithm with memory-based immigration–MIGA

5. RESULTS AND DISCUSSION

Following the obtained results for many combinatorial problems, such as TSP and ATSP [25], where the strategies of immigrations showed their efficiencies, an extension of the genetic approach with immigration strategies in the case of FCTP is carried out. Thus, we applied this approaches to solve some instances of the FCTP problem by using the priority-based representation. First, we use the linear version of the FCTP problem. Therefore, to study the efficiency of the proposed approaches, we compare its performance with the standard genetic algorithm using some randomly generated test problems with different FCTP problem sizes and difficulty levels.

The Table 1 presents the set of parameters considered for different algorithms. Namely, the number of individuals (Npop) in a population, the type of adopted selection (Sel), the choice of crossover (IPX) with its appropriate probability (P_x), the choice of mutation (SWAP) with the appropriate probability (P_m). In addition to the elitism which consist to retaining the best individual from one generation to the next, with the introduced immigration strategy. It should be noted that the adopted choices are the best choices in terms of performance, following the multiple simulations carried out for the different instances and also following the comparisons made between the crossover and mutation operators cited in this article for priority based representation for the FCTP problem.

Table 1. The genetic parameters used in the simulation

	Npop; Sel; X; P_x; M; P_m; insert
Standard genetic algorithm (SGA)	30; Roulette; IPX; 0,6; SWAP; [0.001, 0.2]; Elitism
GA with memory random immigration (RIGA)	30; Roulette; IPX; 0,6; SWAP; [0.001, 0.2]; Elitism + random Immigration (RIGA) after *n* iterations
GA with structured memory-based immigration (MIGA)	30; Roulette; IPX; 0,6; SWAP; [0.001, 0.2]; Elitism + memory-besed Immigration (MIGA) after *n* iterations

The proposed algorithm is tested for standard instances already exploited in previous applications. The programming is done in JAVA (NetBeans IDE 13) on a PC machine with Intel (R) Core (TM) i7-1165G7 2.80 GHz CPU and 8 GB RAM and Windows 10 Professional as operating system. The Figure 7 shows the importance of the integration of the immigration strategies. It influences the improvement towards the optimal solution compared to the standard algorithm, even if we use GA with random immigration (RIGA) or with MIGA.

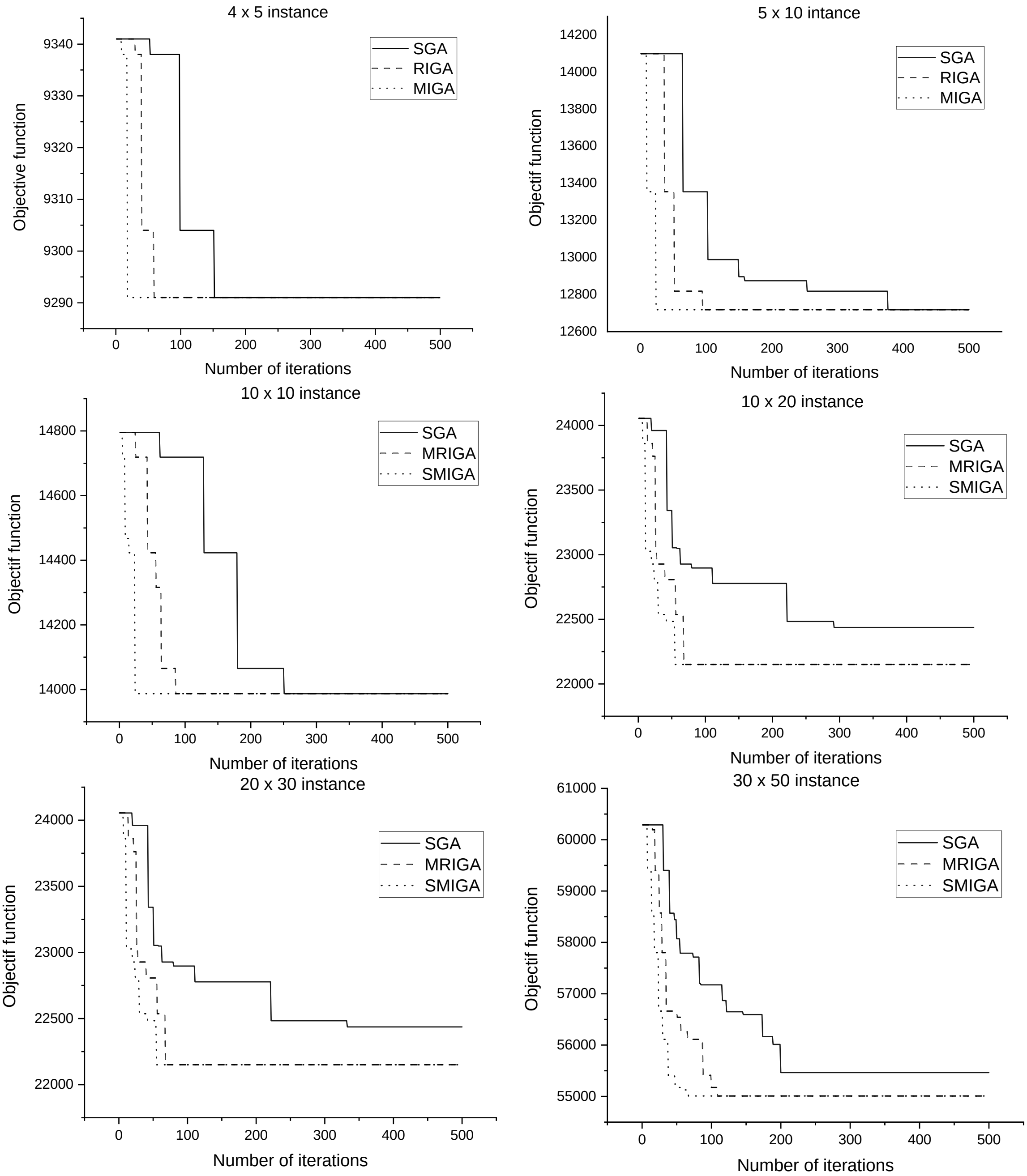

Figure 7. Optimal solution based on the numbers of iterations for the six instances of the FCTP problem

The obtained results show that even in the case of FCTP problem, immigration brings a significant improvement to GA performance as shown in Table 2. Indeed, the same optimal solutions are obtained for small instances (4×5 and 5×10 instances). However, during the genetic process for larger instances, where stagnation posed problem, dynamism is brought to the population when individuals are inserted, randomly or with structured memory, after each interval of time. In addition, we have found a better solution after a smaller number of iterations compared with those obtained with standard GA, in particular, with immigration strategy with structured memory-based immigration.

Table 2. Best and average results by the proposed approach and standard GA for the FCTP problem

Problem size	GA		RIGA		MIGA	
m×n	Best	Average	Best	Average	Best	Average
4×5	9,291	9,291	9,291	9,291	9,291	9,291
5×10	12,718	12,751	12,718	12,734	12,718	12,734
10×10	13,934	14,139	13,934	13,987	13,934	13,987
10×20	22,258	22,531	22,095	22,198	22,095	22,150
20×30	32,683	34,119	32,526	33,234	32,471	32,936
30×50	55,611	56,399	55,007	55,450	55,007	55,269

6. CONCLUSION

In this work, we introduced an immigration strategy to the genetic algorithm to improve its performance to solve the FCTP. Two genetic algorithms based on the principle of immigration are proposed, i.e., genetic algorithm with RIGA and genetic algorithm with MIGA. The two algorithms show the efficiency of the genetic algorithm compared to the standard genetic algorithm. They introduced diversity and dynamism to the population, which made it possible to overcome the stagnation of the fitness function. In addition, the several performed numerical results, for different standard instances, show an improvement in the performance of the genetic algorithm to solve the FCTP problem. Indeed, a better solution is obtained for larger instances in less iterations, especially with the second approach MIGA.

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