A GENETIC ALGORITHM FOR THE SUSTAINABLE SUPPLY CHAIN PROBLEM

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RESUMO

Este artigo descreve o estudo de uma *supply chain*, com ênfase em aplicações relacionadas à sustentabilidade. Devido à necessidade de realizar grandes esforços computacionais para resolver o problema através de um solver exato, é proposto um algoritmo genético que exige menos recursos computacionais, como tempo de processamento. Em mais de 88% dos casos, o algoritmo proposto encontra a solução ótima do problema. No entanto, nos casos em que o problema não é resolvido na otimalidade, o gap de otimalidade é menor que 7%.

PALAVRAS CHAVE. Cadeia de suprimentos, Algoritmo Genético, Rede de Remanufatura.

Área Principal. Logística & Transportes.

ABSTRACT

This article describes the study of a supply chain, focusing on related sustainability applications. Due to the considerable efforts necessary to an exact solver to resolve the problem, a genetic algorithm is proposed, which consumes less computational resources, such as processing time. In more than 88% of cases, the proposed algorithm returns the optimal solution to the problem. Nevertheless, in the cases in which the problem is not solved to optimality, the optimality gap is less than 7%.

KEYWORDS. Supply chain, Genetic Algorithm, Remanufacturing Network.

Main area. Logistics & Transport.

1. Introduction

The environment preservation has been a relevant subject of study in the last years. The discard of contaminants into natural environment has attracted the attention of a huge number of people due to the problems that it may cause to the human life. In addition, the carelessness with nature has been caused many effects, driving countries to damages in the sector of agriculture, fishing and livestock. In some regions in the world, like the European Union, some companies are being encouraged to collaborate with other organizations in the supply chain to guarantee that products can be disassembled and reused, recycled or disposed of safely at the end of their life. A huge number of companies interest in utilise sustainable initiatives like the management of reverse flows due to legal environment restrictions.

The purpose of this work is the present a new logistic system to optimise the recovery process of useless materials (that would be eliminated in the environment), transport them to remanufacturing sites to be recycled and send them to points of sale, where the product may be sold as a new one. A new formulation for this kind of problem will be presented using Genetic Algorithms and the results obtained with the experiments will be shown. The main contributions of this work are:

- We provide an innovative approach for the sustainable supply chain problem
- Our approach improves the perfomance obtained by the IBM ILOG CPLEX solver.

The remainder of this paper is organized as follows. Section 2 reviews related works, while Section 3 defines the sustainable supply chain problem. Section 4 introduces the proposed method based on genetic algorithm and Section 5 presents the results of computational experiments. Finally, Section 6 draws some conclusions obtained in this article.

2. Related works

The use of sustainable strategies in big companies impacts many sectors of the company, affecting from the strategic level to the operational level. In (6), the authors make a link between the facilities location models and the decisions taken in the strategic level in a Supply Chain Management (SCM). A variation of the SCM, the concept of Green Supply Chain Management (GSCM) emerged recently. The GSCM deals with all the processes involved in the lifecycle of a product, from its production to its final use. Furthermore, this concept includes the study of the fabrication of one product with materials that enable a future recycling. However, (7) shows that most part of the references to Green Supply Chain Management are not adequately employed. For this reason, the author defined the notion of GSCM as an environment that covers areas like product design, analysis of materials used in the production, manufacturing processes, transport of the end product to the consumers and the management of the destination of the product, after its lifetime. It was introduced the concept of reverse logistics to help in this last area. In the area of Supply Chain Management, (4) defines the term reverse logistics as “the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in-process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal". In the literature, we can find four different kinds of reverse logistics network: the directly reusable network (DRN), the remanufacturing network (RMN), the repair service network (RSN), and the recycling network (RN). (5) (2) (3).

This article focuses in the Remanufacturing Network (RMN), that is defined as the recovery method of worn products that allows their recycling and enables the production of an unity of the same product with equal quality and utility of the original one. These new recycled goods can be resold as new products. This strategy allows companies to improve their disposal process of old products, reducing production costs and saving raw materials.

In (8), it is presented an approach of the sustainable supply chain problem using Particle Swarm Optimization Algorithm. In this article, we will present a new approach using Genetic Algorithm.

3. Problem Definition

In this paper we study a three-layer location problem for a remanufacturing network. The term remanufacturing represents the process of modification of an useless material, transforming it in a new product with good quality to be marketed as a new item. The remanufacturing activities allows that companies reuse the stock of these old materials to produce new products. The remanufacturing network is composed of three different levels of facilities (we understand facility as a place where it is installed some departments of a company). The first layer represents the sources of material to be sent to the recycling layer. The second layer represents the possible sites where can be installed a remanufacturing facility, where the materials can be modified. Ultimately, the third layer represents the points that will sell the new products, transformed by the remanufacturing layer. The goal of the problem is to determine, among the potential sites of instalation of remanufacturing facilities, the places where these facilities will be installed and the flow of materials between the first and second layers and between the second and third layers. Moreover, we aim to minimize all costs involved, such as the costs for transporting these products and for installing and managing the remanufacturing facilities.

3.1. A model for the sustainable supply chain

The model for the sustainable supply chain problem belongs to the class of localization problems, with three layers. Each layer has a role in the remanufacturing network. The flow in the network is formed by the transport of worn products from the source layer to the remanufacturing layer and by the transport of these materials to the layer that represents the points of sale, after performing the recycling of the products. In this model, we assume that the quantity supplied in the first layer and the quantity demanded in the third layer are known.

The following sets and inputs are introduced:

- I = set of source facilities at the first layer, indexed by i
- J = set of demand points at the third layer indexed by j
- K =set of candidate remanufacturing facility locations at the mid layer, indexed by k
- h_i = supply quantity at source location $i \in I$
- l_j = demand quantity at point of sale location $j \in J$
- f_k = fixed cost of locating a mid layer remanufacturing facility at candidate site $k \in K$
- g_k = management cost at a mid layer remanufacturing facility at candidate site $k \in K$
- c_{ik} = is the unit cost of delivering products at k ∈K from a source facility located in $k \in K$
- d_{kj} = is the unit cost of supplying demand j ∈J from a mid layer facility located in $k \in K$

• $M = \max(\sum_{i\in I} h_i, \sum_{j\in J} l_j)$

We also consider the following decision variables:

• $w_k = 1$, if we locate a remanufacturing facility at candidate site $k \in K$, 0 otherwise
• $x_{ik} = 1$ if the remanufacturing facility located at $k \in$K is serviced by a source facility $i \in$I, 0 otherwise
• $y_{kj} = 1$ f the demand of $j \in$J is serviced by a remanufacturing facility located at $k \in$K, 0 otherwise.

$$\min \sum_{i\in I} f_k w_k + \sum_{i\in I}\sum_{k\in K} h_i c_{ik} x_{ik} + \sum_{k\in K}\sum_{i\in I} g_k x_{ik} + \sum_{k\in K}\sum_{j\in J} l_j d_{kj} y_{kj} \tag{1}$$

s.a:

$$\sum_{i\in I} h_i x_{ik} \leq M w_k \quad \forall k \in K \tag{2}$$
$$\sum_{k\in K} x_{ik} = 1 \quad \forall i \in I \tag{3}$$
$$\sum_{j\in J} l_j y_{kj} \leq M w_k \quad \forall k \in K \tag{4}$$
$$\sum_{k\in K} y_{kj} = 1 \quad \forall j \in J \tag{5}$$
$$\sum_{j\in J} l_j y_{kj} = \sum_{i\in I} h_i x_{ik} \quad \forall k \in K \tag{6}$$

In this problem, the structure of the reverse supply chain is of three layers and we need to decide the quantity, locations of possible remanufacturing facilities. The objective function (1) minimizes the sum of the installation remanufacturing facility costs plus the delivering costs. Constraints (2) warranty that supplying at facility k $\in$ K is delivered to a mid layer remanufacturing facility already opened. Constraints (3) warranty that supplying at facility i $\in$ I must be delivered to only one mid layer remanufacturing facility k $\in$ K. Constraints (4) warranty that the demand of a point of sale facility must be serviced by a remanufacturing facility already opened Constraints (5) ensure that each point of sale facility must be allocated to one remanufacturing. Constraints (6) ensure that the quantity of products being delivered from a remanufacturing facility is equal to the quantity of products being supplied by sourcing facilities.

4. Genetic Algorithm for the sustainable supply chain problem

In this work we propose an approach that explores the features of the Genetic Algorithm (GA). Genetic Algorithms is an evolutionary computation method to solve optimization problems. GA was developed from the analogy with the natural selection. Based in the Darwin's theory of evolution, GA works as the species evolution works. Abstractions of the natural process are done to mechanize the main idea of the algorithm.

4.1. Individual Representation

In 3 we present three decision variables to the problem, the vector w and the matrices x and y. In the GA developed, each individual is composed of these three variables. Instead of using matrices to represent the variables x and y, we utilise vectors to represent them. The decision variables w_k are represented, in the GA, by a binary vector, that indicates if a remanufacturing facility will be installed in the site represented by the index k (in this case, $w_k = 1$) or if in this place no facilities will be installed ($w_k = 0$). The decision variables x_{ik} and y_{kj} are modeled in a different way. In the model, the element x_{ik} indicates if the facility i in the first layer supplies products to the facility k in the remanufacturing layer. In this case, we have $x_{ik} = 1$ if this flow in the network exists, otherwise, $x_{ik} = 0$. In our GA, we represent x by a vector that, in the position x_i, keeps the index of the facility to where the remanufacturing facility i will supply materials. In the mathematical representation, the cases where x_{ik} were zero are not stored in the current genetic algorithm, since it is important to keep in memory just the assignments where there are flow of products between two facilities in different layers. Similarly, we utilise the representation y_j. In this case, the element y_j stores the index of the remanufacturing facility that supplies material to the facility j, in the third layer. For example, if we have the element $y_1 = 3$, it means that the facility represented by the index 1, in the third layer, receive products from the remanufacturing facility, indexed by 3. This representation aimes to minimize the quantity of information stored in the RAM memory, since the quantity of individuals in each iteration may be high.

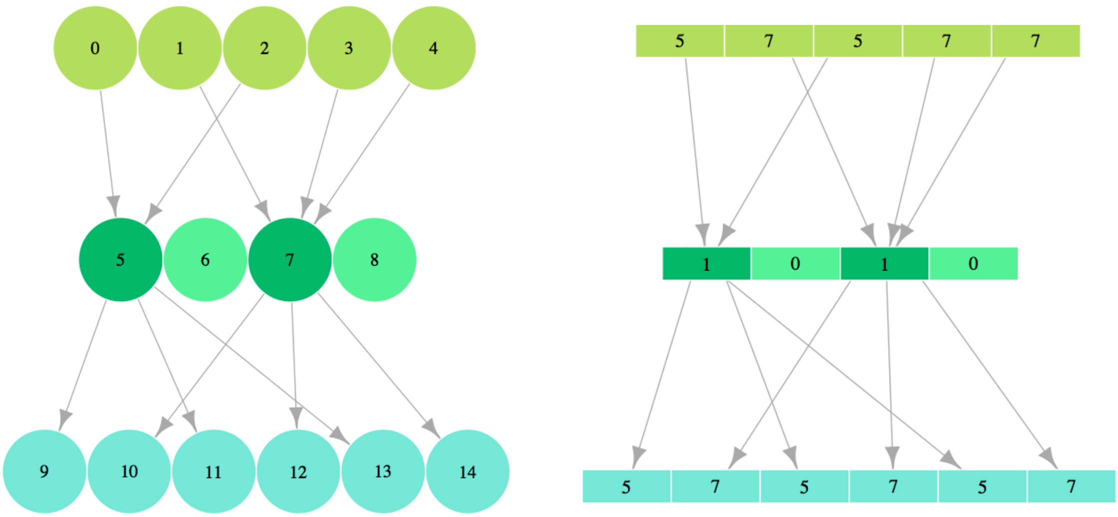

Figura 1: In the left, the figure ilustrates the example of a remanufacturing network with 5 facilities in the first layer, 4 candidates sites where remanufacturing facilities can be installed and 6 facilities in the third layer. In the remanufacturing layer, the points marked as dark green represent the sites were remanufacturing facilities will be installed. In the right, we can see the same network represented in the GA. In the elements of the first layer, we store the indices of the remanufacturing facilities where products will be sent to be recycled. In the same way, in the third layer we keep the indices of remanufacturing facilities that send products to these points. The elements of the vector that represents the remanufacturing layer shows if some facility will be installed in these points, assigning with the integer 1 if the instalation will be made and 0, otherwise.

4.2. Fitness of an individual

The quality of an individual is measured by its fitness. In this problem we aim to minimize all the costs involved in the transport of products and installation of remanufacturing facilities. Each individual has a fitness that measures the cost that this solution represents in the scenario of the problem. For this, we utilize the objective function presented in the Equation 1 in the model to calculate this cost. The minimum the cost of the solution, the better the individual is.

4.3. Genetic Operators

One of the main reasons for the diversification of the individuals features in the GA and its quality improvements are the genetic operators, performed in the data structures that represent them. We utilise a tournament selection (1), where k individuals compete to undergo crossover and mutation operations. Below, it will be described these methods used in this work.

4.3.1. Mutation

The mutation process starts with a modification in one point of the vector w. For each one of these points it is generated a random value. If this number belongs to an interval of probability of mutation defined *a priori* the point in the vector w is modified. The mutation of a point in the vector inverts the current binary value, that is, if the current value is 1 the value is changed to 0 and if the value is 0, it is modified to 1. This process is made for all elements in w. However, as we work only with feasible individuals, some special cases must be treated after the perfomance of the mutation procedure.

To ilustrate the mutation procedure, we considere the individual represented by the network of the Figure2 (a). The vector w of this individual has four elements, in which w_2 and w_3 represent the points where two remanufacturing facilities will be installed. We supose that, after performing the mutation in w, the individual has the elements w_3 and w_4 changed (the element w_3 modified to 0 and w_4 changed to 1). After this, the individual represents in the remanufacturing layer that the facilities will be installed in the sites represented by w_2 and w_4. When removing the instalation of a facility in the site w_3, this element can no longer receive products from the first layer. The points in the first layer that were assigned to send materials to w_3 must be changed to send products to the other points marked as place of installation of remanufacturing facilities. Due to this restriction, the element 3 in the first layer must be assigned to the remanufacturing facilities w_2 or w_4. In this case, as the remanufacturing facility w_4 do not receive any materials from the first layer, it now receives products from the point 3 of the first layer. In the same way, the elements of the third layer that were assigned to the remanufacturing facility w_3 start to receive products from the points where there is a remanufacturing layer installed. The Figures 2 (b), 2 (c) and 2 (d) show possible assignments to the facilities 3 and 4, of the third layer. The algorithm choses, among all the possible solutions, the one that gives the individual with the best fitness.

4.3.2. Crossover

The crossover procedure is an operation performed between two individuals of a population. These individuals, known as parents, generate two other individuals to the population

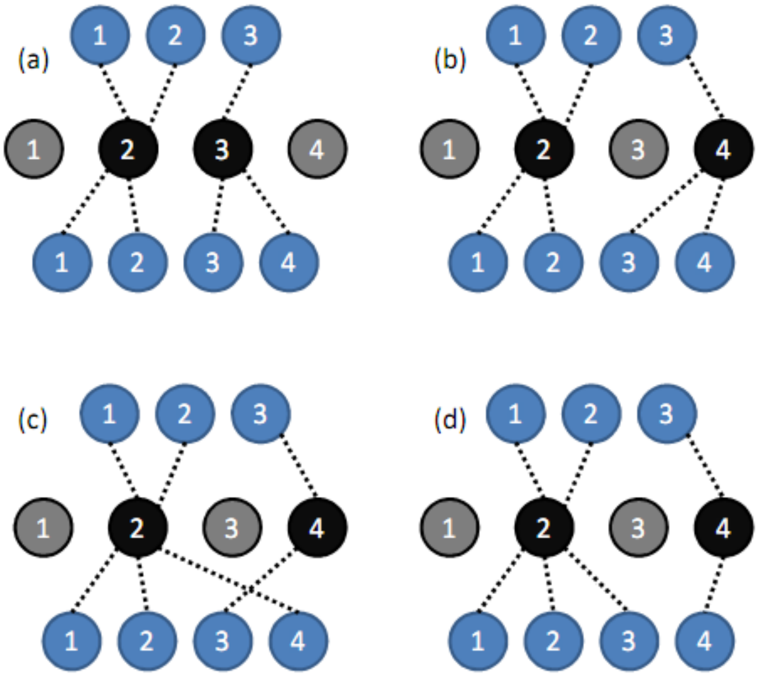

Figura 2: Mutation of an individual

of the next generation. The first step of the process is to determine the two individuals to suffer the crossover, using the selection method, and to define the point in the individual that will be made the crossover. This point is known as cut point. In the genetic algorithm the cut point is chosen randomicaly e it refers to a point in the vector w. To ilustrate the process, we show the parents Ind_1 and Ind_2 in the Figures 3 (a) e 3 (b), respectively. The crossing point chosen is the point 2 (the cut between the elements 2 and 3 of the vector). The first individual generated has the beginning of the vector w of the individual Ind_1 and the final part of Ind_2 (Figure 3 (c)). The term beginning of the vector w indicates the segment of w from the start point to the cut point. The same is valid for the term final part of w. It indicates the segment from the cut point to the last point in the vector. The assignments between facilities of different layers of the individual generated respect some rules. The assignments from the first layer of the individual represented in the Figure 3 (c) were created as follows: for each element of w, the assignments of the facilities in the parents are sent to the new individual created. As we can see in the Figure 3 (c), the third facility of the first layer has no assignments originated from the parents. This facility must be allocated to one of the two remanufacturing facilities installed (the assignments highlighted show possible appointments). In the same way, the element 4 in the third layer is not assigned to any remanufacturing facility. This fact enables its assignment to one of the two points with remanufacturing facilities installed in w. The algorithm choses the assignment that has the best fitness among all combinations. The final individual can be seen in the Figure 3 (e). The second individual generated can also be seen in the Figure 3 (d). We can observe that the point 4 of the remanufacturing layer (chosen to install a facility) is not assigned to any facility. To solve this problem, the algorithm choses one of the assignments made to one of the points of w that will be installed a remanufacturing facility and transfer it to the point without assignment. The second final individual can be seen in the Figure 3 (f).

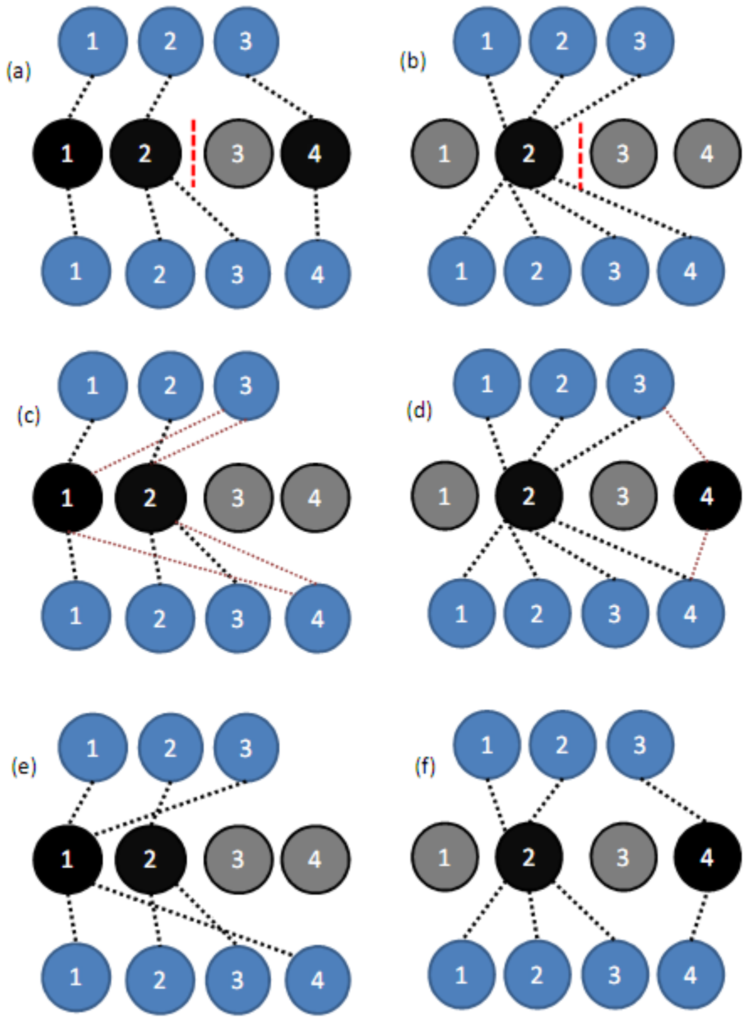

Figura 3: Crossover between two individuals

4.4. Validation of individuals

The genetic algorithm developed deals with feasible individuals, i.e., all individuals in the population must respect the constraints imposed by the problem. To ensure that all individuals inserted in the population are feasible, a validation method is created. This method identify where the failure is and repare this error. To better understand how this method works, we show an exemple of the algorithm. We supose a network with 6 possible sites to install the remanufacturing facilities, where 4 of these sites are represented as chosen in the individual. The vector w of this individual is represented by $w = [\ 0\ 1\ 1\ 0\ 1\ 1\ ]$. Consider that each site in the remanufacturing layer will receive the the quantity of products $in_0 = 0$, $in_1 = 20+30$, $in_2 = 40$, $in_3 = 0$, $in_4 = 20$ and $in_5 = 30+20$, where in_i indicates the quantity of material sent from the facilities in the first layer to the site i in the remanufacturing layer (clearly, if $w_i = 0$, then $in_i = 0$). Similarly, we consider that each point in the remanufacturing layer sends to the third layer the quantities $out_0 = 0$, $out_1 = 30$, $out_2 = 40$, $out_3 = 0$, $out_4 = 20$ e $out_5 = 70$. In short, the individual created has the vectors $in = [\ 0\ 50\ 40\ 0\ 20\ 50\ ]$ and $out = [\ 0\ 30\ 40\ 0\ 20$

Tabela 1: GA Parameters

Parameter	Value
Number of generations	10
Number of individuals	100
Crossover rate	70%
Mutation rate	30%
Elitism	5%
Tournament size	5

70].

Firstly, the algorithm calculates the difference $dif = in - out$, that is $dif =$[0 20 0 0 0 -20]. There are some elements in dif with values different of zero. In this case, we have that the individual does not ensure that the quantity of material received by a remanufacturing facility is equal to the quantity of material sent by it to the point of sale. After identifying the failure, the algorithm performs a local search, trying to do changes in the assignments between the first and the remanufacturing layers or between the remanufacturing and third layers. In this case, the algorithm identifies a rest of 20 unities in the remanufacturing point 1 and a deficit of 20 in the point 5. After that, the assignment that was sending 20 unities to the remanufacturing facility 1 starts to send these materials to the remanufacturing facility 5. In this moments, the vectors *in* and *out* have that same values, resulting in the vector dif with all elements equal to zero. In this case, the method enables the feasibility of the individual in one step. However, it is not always possible to do in one step. The algorithm works until the values in dif are different of zero.

5. Computational Results

To verify the efficiency of the genetic algorithm developed, extensive experiments were performed in different scenarios. To compare the results obtained in the executions of the GA we solved the exact model in the solver CPLEX, for all instances. The Figure 4 shows the results and the execution time obtained in the execution of the genetic algorithm with a set of parameters and the results and times found in the execution the solver. To measure the quality of the solutions of the GA, is presented the average of 10 executions for each instance. In the experiments we tested many set of parameters of the GA. The set of parameters used is shown in the Table 1.

We can observe that, as expected, the execution time of the genetic algorithm is less than the time to solve with CPLEX, in most cases. The first graph in the Figure 4 shows the results obtained in the execution of the GA and CPLEX. For each instance, we present three columns. The first column is the result of the solver, the second is the average of the results obtained in 10 executions of the GA and the third column is the best solution reached among the 10 executions. The GA found the optimal solution in 88% of the instances tested, at least in one of the executions. In the instances where the genetic algorithm could not find the optimal solution, the worst optimality gap found was 6.42%. The second graph in the Figure 4 presents the execution time of the CPLEX and the average of the 10 executions of the GA. This graph is plotted in a logarithmic scale, since the diference between the execution time of the two approaches may be huge. For instance, in the scenario represented by the instance 14 the time spent by the GA was 6.61s and the 1514.05s. We observe a difference of more than 200 times in the efficiency.

6. Conclusion

In this article we present a new approch for the sustainable supply chain problem. The problem belongs to the class NP-hard and it consists in to decide where to install remanufacturing facilities in a three-layer network. These layers represents the facilities of source of products, the possible sites for installing remanufacturing networks and the facilities of demand. They send products among them, with transport costs involved. In the source points and in the facilities of sale the quantities of offer and demand of products are known. The problem is solved using genetic algorithm, a metaheuristic that enables many applications and allows us to find good solutions, specially in hard problems.

The genetic algorithm developed deals only with feasible solutions, that is supported by a validation function of individuals. This function has the role of treating the constraint that ensure that the quantity of products that arrives in a remanufacturing facility is the same quantity that is sent from this facility. Extensive experiments were performed to present the efficiecy of the algorithm. To verify the quality and the execution time of the solutions obtained with the genetic algorithm we solved the instances in the optimality, using the solver CPLEX. In more than 88% of instances, the genetic algorithm reaches the optimal solution of the problem. However, in the other cases, the optimality gap is less than 7%. We can also observe the efficiency of the GA in many instances. In some cases the GA reached the optimality in a execution time more than 200 times faster than the execution in the CPLEX.

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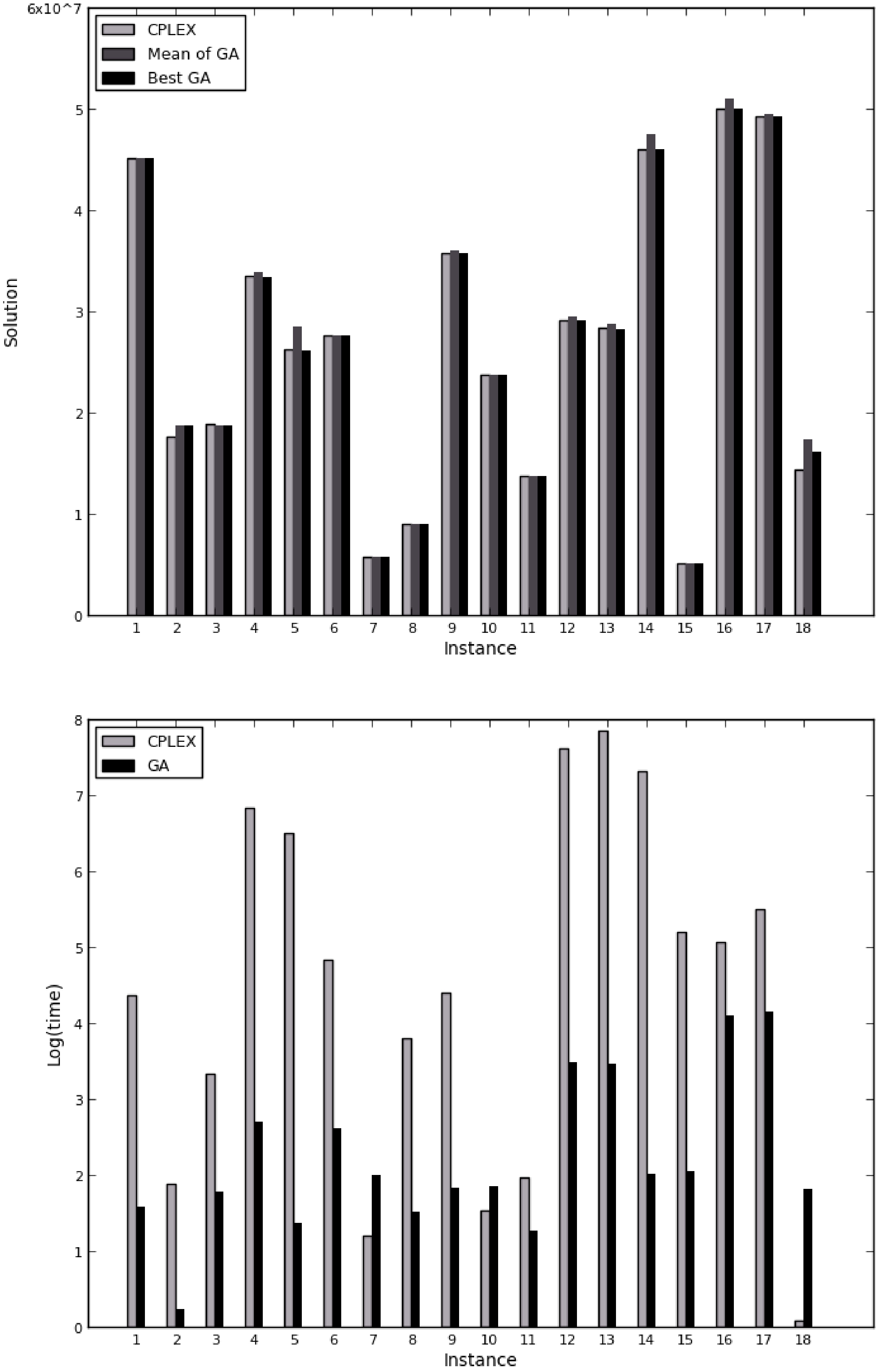

Figura 4: Results obtained in the experiments.