DEVELOPMENT OF A GENETIC ALGORITHM FOR THE SOLUTION OF A LOAD ALLOCATION PROBLEM

Natalia Alejandra Gelves Tello
Candidate for the Master's Degree in Industrial Engineering
Pontificia Universidad Javeriana
Carrera 7 No. 40 – 62
Bogotá-Colombia
gelves.n@javeriana.edu.co

Mónica Patricia Acosta Rodríguez
Candidate for the Master's Degree in Industrial Engineering
Pontificia Universidad Javeriana
Carrera 7 No. 40 – 62
Bogotá-Colombia
acostamonica@javeriana.edu.co

Juan Pablo Caballero Villalobos
PhD in Engineering
Universidad de los Andes
Director of the Master's Degree in Industrial Engineering
Pontificia Universidad Javeriana
Carrera 7 No. 40 – 62
Bogotá-Colombia
juan.caballero@javeriana.edu.co

Abstract.

The purpose of the present study case was to determine the best feasible solution for a typical load allocation problem with different constraints associated with the technical conditions of the case. The model proposed intends to maximize the profits when transporting the loads, by an adequate transport plan, according to the capacities of the vehicles, the characteristics and the demand of the loads. Taking into account the magnitude of the problem and its computational complexity, to solve the problem. The Metaheuristic Genetic Algorithms were implemented, which allows solving problems of optimization and search. The algorithm was developed in Visual Basic for Applications, defining and creating an initial feasible population, from which it proceeds to develop the entire evolutionary process associated with the genetic algorithm. Finally, the results were compared with those obtained at the GUSEK software, which offers the optimal solution for the allocation problem studied. From this comparison, it is evident that the method developed in the present research offers feasible solutions very close to the optimal one with a computational cost considerably lower than offered by the GUSEK program.

Keywords.

Genetic Algorithm, capacity, Heuristic, Load allocation problems.

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1. Introduction and Justification

The load allocation problem seeks to maximize profits by allocating the loads that must be delivered to customers in different compartments of vehicles belonging to a particular transportation company. This problem is based on the Bin Packing Problem (BPP), which consists of packing a set of n objects, with different weights w_i with $i = 1,2,3, \dots, n$, in different containers such that the weight and / Or total volume does not exceed the maximum value of the containers (Daza, Montoya and Narducci, 2009). An extension of the BPP is the known Cutting Stock Problem (CSP), which adds a demand value for each object, defined as d_i con $i = 1,2,3, \dots, n$, (Delorme, Iori, and Martello, 2016). In order to achieve this goal, the algorithm seeked for the total demand using the smallest number of containers. These problems are extensively worked and reviewed in the literature because their computational complexity places them in the category of NP-HARD problems (Brandão and Pedroso, 2015). Meaning that the application of approximate solution methods is widely used for the improvement of problem solving.

Genetic algorithms are a subclass of evolutionary algorithms, which have been studied and developed efficiently for their robustness, in solving several optimization problems. It’s a metaheuristic optimization based on a population and uses mechanisms inspired by the biology of evolutionary optimization inspired by Darwin and his law of evolution. It's composed of three major biological evolutionary mechanisms: selection, mutation and crossover (Pan That Pann Phyu, Srijuntongsiri, 2016).

At these algorithms, solutions or individuals are encoded in gene or chromosome strings. A fundamental feature of these algorithms is that they work with a set of solutions that simulate a population. As a first step, an initial population is randomly created, then each element of the population is evaluated by means of the adaptation or fitness value assignment to quantify each solution taking to a consideration, the other solutions in the population. Next, if the stopping criterion is not met, the adaptation value is used by a random selection procedure with a bias toward individuals with better fitness to produce a set of parents that will be used by a crossover operator to generate New solutions (Díaz, Pinto, Vom Lücken, 2013).

Genetic Algorithms offer the following advantages over any other conventional solution method (Hasancebi and Erbatur, 2000):

1. It does not require derivatives on the functions.
2. It uses a population of search points greater than one, which guarantees the existence of a set of feasible solutions with a greater probability of containing the global optimum.
3. Maintains a set of potential solutions in each generation.
4. It allows to consider search spaces that consist of a mixture of continuous and discrete variables.

In addition to this, the probabilistic nature of Genetic Algorithms minimizes the possibility of converging to local optimum (Javadi, Farmani and Tan, 2005).

This work will be presented as follows, in the section 2, description of the problem and the mathematical model used for the algorithm. Then at the section 3, the authors showed some literature review that allows to specify the importance of this study. At section 4, we described how the algorithm was applied. Ends with the application and results in the section 5 and the conclusion in section 6.

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2. Description of the problem

Within the BPP, there are problems that have multiple restrictions, known in at the literature as allocation problems (Brandão, et al., 2016); So that, it's sought to minimize the number of containers to be used taking into account the set of service restrictions that have and the need to satisfy the demand at the lowest cost. In the present work, the authors solved an allocation problem with the following technical characteristics.

"A company has several vehicles, each of which has k compartments. Each compartment is designed with limited capacity in terms of volume and weight that can carry. It´s desired to transport several types of cargo, of which the volume density (kg / m3), the quantity to be transported (kg), the gain obtained for each unit transported ($ / kg), a cost ($) Each load in each vehicle (the same is charged regardless of the amount transported). For transportation purposes, the fillers may be fractionated and mixed together; However, there're restrictions that prevent some loads can be carried in the same compartment and if they're loaded in the same vehicle, it's obligatory to pay insurance ($) for this practice (the amount of the insurance policy to transport each pair of charges i and j. In the same vehicle is fixed, does not depend on the quantities transported). There're restrictions that prevent transportation in the same vehicle. In order that the vehicle doesn't present problems in its operation, the compartments must use the same ratio of transported weight / carrying capacity of weight. In addition, the company has categorized its vehicles (a vehicle can belong to several categories), and has established for each category only a maximum number of vehicles may be carrying cargo. Finally, it must be satisfied that: if the vehicles 7 and 5 render the service, and the 10 does not render the service, then the vehicle 1 must render it. The objective is to determine the transportation plan to maximize the profit for the company when transporting the loads ".

From this, the following mathematical model is established:

Set
Categories: **S**
Vehicles: **V**
Compartments: **C**
Loads: **F**

Parameters.
Volumetric capacity of vehicle v compartment c: $Vol_{v,c}$
Load capacity of vehicle v compartment c (kg): $Pes_{v,c}$
Volumetric Density of Load f: den_f
Quantity in (kg) of the load f available to transport: $Oferta_f$
Gain by ($ / kg) of the load f: g_f
Fixed cost for transporting load f in the vehicle v: $Cfc_{f,v}$
Binary: 1 if load f cannot be transported in the same compartment as load g, or otherwise 0: $restc_{f,g}$
Binary: Val seg-kg if insurance must be paid for transporting cargo f and g in the same vehicle, or otherwise 0:$seg_{f,g}$
Binary: 1 if it is forbidden to carry loads f and g in the same vehicle, or otherwise 0: $ban_{f,g}$
Binary: 1 if vehicle v belongs to category S, or otherwise 0:$catveh_{v,s}$
Maximum number of vehicles of category s that can be used for transport: $maxuse_s$

Variables

Quantity of cargo f transported by vehicle v in compartment c: $x_{f,c,v}$

Binary, if charge f is carried in vehicle v in compartment C, otherwise 0:$y_{f,c,v}$
Binary, if load f and load g is carried in vehicle v, or otherwise 0:$w_{f,g,v}$
Binary, 1 if vehicle v is used to transport cargo, or otherwise 0: Ψ_v
Binary, 1 charge f is carried in vehicle v, or otherwise 0: $\delta_{f,v}$

Objective function

$$\max z = \sum_{\forall f\in F}\sum_{\forall c\in C}\sum_{\forall v\in V} g_f * x_{f,c,v} - \sum_{\forall f\in F}\sum_{\forall v\in V}\delta_{f,v} * Cfc_{f,v} - \sum_{\forall v\in V}\sum_{\forall f\in F}\sum_{\forall g\in F} seg_{f,g} * w_{f,g,v} \quad (1)$$

Restrictions

$$\sum_{\forall v\in V}\sum_{\forall c\in C} x_{f,c,v} \le oferta_f \quad \forall f \in F \; (2)$$
$$\sum_{\forall f\in f}\frac{x_{f,c,v}}{den_f} \le vol_{v,c} \quad \forall v \in V \quad \forall c \in C \; (3)$$
$$\sum_{\forall m\in M} x_{f,c,v} \le Pes_{v,c} \quad \forall v \in V \quad \forall c \in C \; (4)$$
$$y_{f,c,v} \le x_{f,c,v} \quad \forall f \in F \quad \forall v \in V \quad \forall c \in C \; (5)$$
$$MY_{f,c,v} \le x_{f,c,v} \quad \forall f \in F \quad \forall v \in V \; (6)$$
$$\delta_{f,v} \le \sum_{\forall c\in C} x_{f,c,v} \quad \forall f \in F \quad \forall v \in V \; (7)$$
$$M\delta_{f,v} \le \sum_{\forall c\in C} x_{f,c,v} \quad \forall f \in F \quad \forall v \in V \; (8)$$
$$\delta_{f,v} + \delta_{g,v} \le 1 + (1 - ban_{f,g}) \quad \forall f \in F \;\; \forall g \in F \;\; \forall v \in V \; (9)$$
$$Y_{f,c,v} + y_{g,v,c} \le 1 + (1 - restc_{f,g}) \quad \forall f \in F \;\; \forall g \in F \; \forall c \in C \; \forall v \in V \; (10)$$

$$\delta_{f,v} + \delta_{g,v} \le 1 + w_{f,g,v}) \quad \forall f \in F \;\; \forall g \in F \;\; \forall v \in V \; (11)$$

$$\Psi_v \le \sum_{\forall f\in F}\delta_{f,v} \quad \forall v \in V \; (12)$$
$$M\,\Psi_v \le \sum_{\forall f\in F}\delta_{f,v} \quad \forall v \in V \; (13)$$
$$\sum_{\forall v\in V}\Psi_v * catveh_{v,s} \le mause_{,s} \quad \forall s \in S \; (14)$$

$$\sum_{\forall f\in f}\frac{x_{f,c,v}}{Pes_{v,c}} = \sum_{\forall f\in F}\frac{x_{f,d,v}}{Pes_{v,d}} \qquad \forall v \in V \qquad \forall c \in C \;\; \forall d \in C \; (15)$$

$$\Psi_7 + \Psi_5 + (1 - \Psi_{10}) \le \Psi_1 + 2 \quad \forall 5,7,10,1 \in V \; (16)$$

$$x_{f,c,v} \ge 0 \;\; \forall f \in F \; \forall c \in C \; \forall v \in V \; (17)$$

3. Literature Review

Within the literature, it has been found different approaches to solve the problem of resource allocation. It should be noted that these problems can be associated with logistical areas such as the allocation of loads to vehicles, environmental areas such as the allocation of garbage, manufacturing areas for the assignment of tasks to different machines or operators, and even in electric areas such as the allocation of electricity to consumers (Alayande, Jimoh, Yusuff and Awosope, 2015).

Wei-long and Qing (2007) implemented the metaheuristic Genetic Algorithms to solve the stochastic location-routing problem (SLRP). Through the implementation, they divided the problem into two sub problems, one associated to the stochastic assignment of the loads to the transport vehicles through the location allocation problem (LAP) and the other one, associated to the allocation of the routes with lower costs through the solution of a Stochastic Vehicle routing problem (SVRP). From this research they

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concluded that the application of Genetic Algorithms to logistic problems such as the LRP, which contains the problem of resource allocation, generates high quality solutions because the local search and the elitist crossing operator, which selects The best parents and children for the generation of the new population; Associated with metaheuristics improve the intensification phase while strategies associated with mutation aid in diversification, minimizing the probability of falling into local optimum.

Sharifi, Fang and Afshar (2010) solved the Waste Load Allocation (WLA) problem by implementing the Ant Colony Optimization (ACO) metaheuristic in a negotiation algorithm, where garbage suppliers could negotiate based on their goal of minimizing cost while all complied with the environmental restrictions associated with the maximum amount of garbage allowed in the different aqueducts. This research, highlights the ability of different approximate solution methods to offer feasible solutions; In addition, the solutions constructed by the different ants participating in the ACO metaheuristics are similar to the chromosomes in the Genetic Algorithms (Sharifi, et al., 2010).

Gargiulo and Quagliarella (2012) solved a resource constrained project scheduling problem (RCPSP) by developing five genetic algorithms focused on the problem of assigning the different tasks to the participants in the project, considering the restrictions of origin, dependence and time. Through the application of the different genetic algorithms developed, it’s possible to conclude that the proper introduction of the different genetic operators and selection and the inherent characteristics of the problem, can offer high quality solutions in more efficient times.

Alayande, et. To (2015) show that the problems associated with the distribution of electric power can be seen as problems of allocation of loads by the implementation of an allocation matrix, which shows the structural interconnections of the network. This is how they offer a new approach to solving the energy flow problem from a resource allocation perspective. From this, it can be concluded that research associated with the problems of resource allocation have a great application in different areas and areas, as long as it’s possible to determine precisely the objective and the mathematical model to solve the problem.

According to the study by Khelifi, Saidi and Boudjit (2016) on the efficient design of network topologies with the Problem of Design of Qualified Networks (CNDP) with modular linking capabilities to design networks of minimum cost and to satisfy the demands of flow. They proposed a model based on Genetic Algorithm (GA) of two levels that can work with diverse variations of the CNDP. The objective was to minimize three criteria: marginal cost, modules and routing. Since it's a trained network design, it's defined as an NP-HARD problem; These models consider a graph composed of nodes and edges. For a better use of these resources, network designers have had to solve the CNDP, which consists of selecting edges and the optimal capacities to assign a set of goods between origin and destination pairs. Each merchandise is defined by a source node, a destination node and by the amount to be routed. The combination of genetic algorithms and linear programming to solve the problem at two levels is more effective than the iterative local search approach, since it determines solutions close to the best known ones. This proposition defined a new coding scheme to deal with the modular case.

4. Methodology

In the present investigation, the metaheuristic of Genetic Algorithms was implemented to give solution to the problem of allocation previously proposed. The development of this metaheuristic was made by using Visual Basic for Applications (VBA) in Excel 2010.

Next, the steps corresponding to the developed Algorithm are presented:

- Definition and creation of the initial population
- Performance measurement

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- Selection
- Crossing and Generating children
- Mutation

In the following figure can see the development of the genetic algorithm:

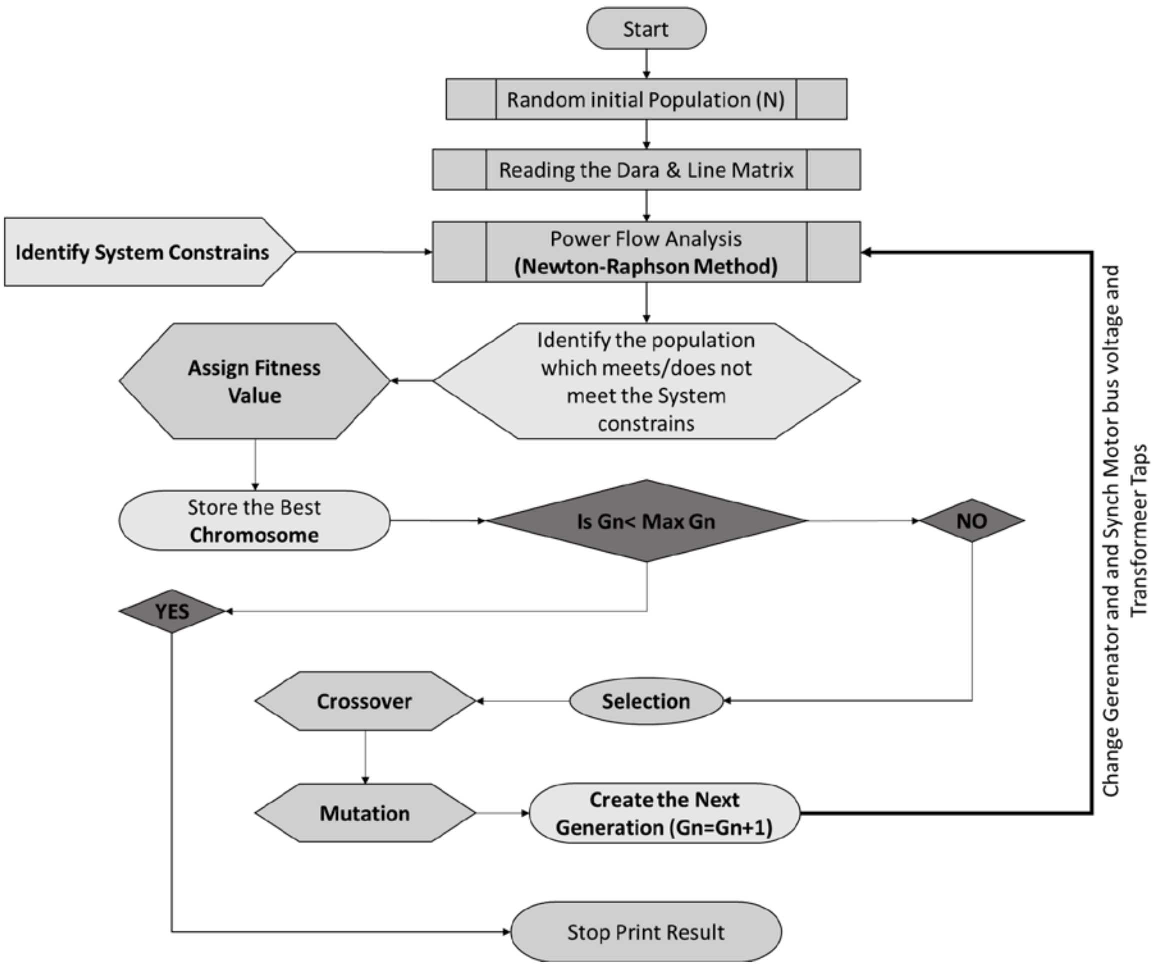

Figure 1. Flow diagram of the evolution process of a GA algorithm, Taken from (Al-Hajri, Abido y Darwish, 2015).

4.1 Chromosome Structure

The success of a Genetic Algorithm lies in the representation of the individual and the creation of the initial population, to initiate the exploration in the search space. Contextualizing the specific characteristics of this model, we have the following definitions:
Population: Set of all individuals.
Individual: Solution to the problem, for this specific case are 5 vectors.

1 vector: Loads defined as f
2 vector: Vehicles
3 vector: Compartments c
4 vector: Categories S

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5 vector: Value of how much should be charged.
Gene: Set of values that make up the chromosome. Position n within the vector
Chromosome: Sequence of genes that establishes the characteristics of the individual.
The initial population is generated and filled with individuals at random, with integer values (Renner and Ekárt 2003), the scope of a GA is to obtain accurate solutions.

Table 1. Individuals for the Assignment problem.

f	**v**	**c**	**s**	**Size**
1	2	1	1	50
1	2	2	4	20
1	5	1	3	30
1	7	5	2	15

Population Size:
To avoid incurring risks of not adequately covering the search space, or an excess of computational cost, the algorithm will generate 100 individuals as the initial population. According to Roeva and Fidanova (2013), in their study determined that this population is adequate, due to the parameters and that the data were obtained in a reasonable time and did not affect the quality of the same.
For creating the initial population, the gradient considered were supply, volume, weight and balance restrictions.

4.2 Performance Measurement:

For performance measurement, a feasibility check is performed by reviewing compliance with the constraints posed for the problem and the objective function is evaluated. In this specific case, it's to maximize the profit for the company when transporting the loads. For this purpose, the objective function (1)

$$\max z = \sum_{\forall f \in F} \sum_{\forall c \in C} \sum_{\forall v \in V} g_f * x_{f,c,v} - \sum_{\forall f \in F} \sum_{\forall v \in V} \delta_{f,v} * Cfc_{f,v} - \sum_{\forall v \in V} \sum_{\forall f \in F} \sum_{\forall g \in F} seg_{f,g} * w_{f,g,v} \quad (1)$$

The probability of survival of an individual is determined by his fitness condition. Individuals with higher fitness are those who are more frequently chosen than individuals with worse values (Renner and Ekárt, 2003).

4.3 Selection

For the selection of individuals of the next generation, values are organized from highest to lowest and the tournament method is used. The celebration of a tournament between s competitors, where s represents the size of the tournament, is generated guarantying that the individual with the highest value in the objective function of the competitors will be the winner of said tournament and will be termed as "father" Of the next generation.
In this study the tournament is carried out with 2 competitors, where two random individuals are chosen by means of a probabilistic selection and, later, to choose the best of them, which will be denominated as

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"father". Tournament selection is a useful and robust selection mechanism commonly used by genetic algorithms (Miller and Goldberg, 1995).
The random selection technique works by generating two random integers, each representing a chromosome. The two fitness values of the randomly selected chromosomes are compared and the one with the best fitness value is to be considered for this stage. This mechanism of randomly selected chromosomes will be repeated until the population at this stage is equal to the initial population of the chromosomes (Al-Hajri, Abido and Darwish, 2015).

4.4 Crossover

New individuals are usually created as the offspring of two parents. In order to carry out the offspring, it becomes necessary to specify how the parents' chromosomes will be combined, so that the crossing operator is developed. This operation can be performed in different ways, Figure 2 shows the so-called crossing at one point and Figure 3 shows the crossing at two points. According to the literature, the two-point crossing of a higher probability of better individuals with respect to crossing a single point (Hasancebi, et al., 2000).

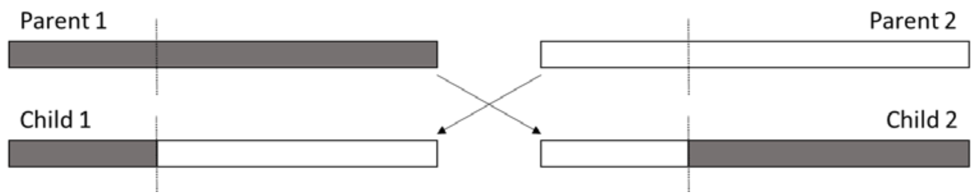

Figure 2. 1-Point Crossover

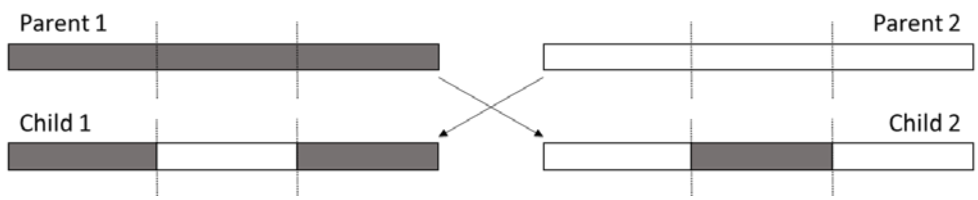

Figure 3. K point Crossover

The crossing strategy for this problem consisted of taking two points from the parents, selected in the previous step to build their offspring. Next, the crossing strategy was implemented for the solution to the problem which is shown at Figure 4.

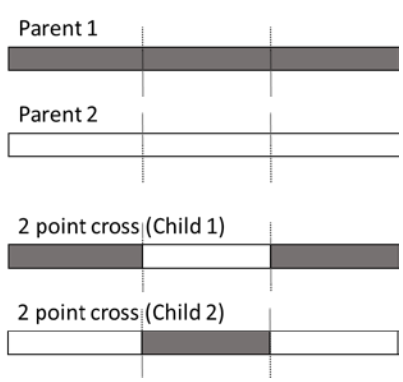

Figure 4. K point Crossover. Generation of Children.

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A second population of children is generated to avoid making penalties to unfeasible individuals and this is achieved, eliminating those who are not feasible.

4.5 Mutation

The mutation is considered as a basic operator that provides a small element of randomness into the neighborhood of individuals belonging to the population. For this case, the Step Mutation or Uniform Mutation was used, which applies to the children. The mutation is performed as long as the individual has a mutation probability greater than 30%.

The Step Mutation is applied only when the encodings are real and integer, making a random choice of a coordinate within the chromosome, so that, it changes its value for another between the current and one end of the range of possible values can take the variable. For proper implementation of the Step Mutation, a random coordinate must be chosen within the selected individual, a direction of random change is established (towards the maximum or towards the minimum of the possible values that the variable can take), the new value to place in the coordinate between the current value and the extreme (Kim and Asce, 2012).

The generation of mutated children is checked for feasibility by evaluating the objective function and constraints. After performing these steps, the mutated parents and children are organized from major to minor, respecting the value of their objective function, and the first 100 individuals are selected; Thus having the new population, which corresponds to the same size of the initial population.

4.6 Detention Criteria

The detention criteria for the present algorithm was based on the number of generations created. The maximum number of generations used was 100. From this, the algorithm performs 100 iterations of the problem and gives the best solution of the solutions offered in each iteration.

5. Analysis and Results

In order to verify the adequate performance of the algorithm developed in the present investigation, two instances (See Annex 1) were designed for each could be solved by GUSEK software (GLPK Under Scite Extended Kit) version 0.2, in order to obtain the optimal solution of each one of them; And through the implementation of the presented genetic algorithm. The instance denominated P contemplates three vehicles with three compartments each, belonging to three different categories and three types of loads; While the instance called G contemplates fifteen vehicles with three compartments, which have five different categories and an amount of fifteen loads.

From this, Table 2 presents the results of the GUSEK Software and the algorithm developed for the two instances used. For the instance P, the solution offered by GUSEK yielded a target function value of $ 21,590.43, using compartments 1, 2 and 3 of vehicle 3, for load 3; While the objective function value thrown by the developed algorithm was $ 20,129, using the same vehicle and the same compartments to carry the load of the optimal solution offered by GUSEK. As for instance G, it can be seen that the value of the objective function thrown by the GUSEK software was $ 10,858.97, using the compartments 1, 2 and 3 of the vehicle 1 to carry loads 3, 11 and 15, the Compartments 2 and 3 of the vehicle 2 to carry the load 11, and the compartments 1, 2 and 3 of the vehicle 4 to carry the load 11; Finally, the developed algorithm obtained a target function value of $ 9,293.46 using the same compartments of the same vehicles to carry the same loads of the optimal solution offered by GUSEK.

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By the results obtained in the application of the developed algorithm, it can be observed that, for the instances P and G, the algorithm did not find the optimal solution but the maximum percentage difference presented between the solutions thrown by the algorithm and those offered by the software was of 14.42%, this being that of instance G, while for instance P was 6.78%. In addition to this, it can be concluded that the genetic algorithm developed in this research, assigns loads to behaviors and vehicles identically to the optimal allocation, differentiating only the amount of load to be carried, but which, as mentioned previously, does not present a significant percentage difference in the value of the objective function. Finally, it should be noted that this percentage difference is not significant if one considers the computational saving offered by the algorithm in the solution to the problem

Table 2. Results obtained through the use of the GUSEK software and the implementation of the Genetic Algorithm developed.

Instance	Load to carry (kg)	Vehicle Used	Compartment Used	Value Function Target GUSEK($)	Value Function Target Genetic Algorithm ($)
Instance P.	Load 3 (210,476)	Vehicle 3	Compartment 1	21590.42857	
	Load 3 (200)	Vehicle 3	Compartment 2		
	Load 3 (286,667)	Vehicle 3	Compartment 3		
Instance P.	Load 3 (220)	Vehicle 3	Compartment 1		20129
	Load 3 (210)	Vehicle 3	Compartment 2		
	Load 3 (220)	Vehicle 3	Compartment 3		
Instance G.	Load 3 (47,64)	Vehicle 1	Compartment 1	1,085,896,962	
	Load 3 (51,3778)	Vehicle 1	Compartment 3		
	Load 11 (51,0239)	Vehicle 1	Compartment 1		
	Load 11 (50)	Vehicle 2	Compartment 2		
	Load 11 (50,3413)	Vehicle 2	Compartment 3		
	Load 11 (42,8328)	Vehicle 4	Compartment 1		
	Load 11 (48,2935)	Vehicle 4	Compartment 2		
	Load 11 (50)	Vehicle 4	Compartment 3		
	Load 15 (53,33)	Vehicle 1	Compartment 2		
Instancia G.	Load 3 (49,8)	Vehicle 1	Compartment 1		9293,46
	Load 3 (50,02)	Vehicle 1	Compartment 3		
	Load 11 (50,02)	Vehicle 1	Compartment 1		
	Load 11 (50)	Vehicle 2	Compartment 2		
	Load 11 (49,8)	Vehicle 2	Compartment 3		
	Load 11 (45,06)	Vehicle 4	Compartment 1		
	Load 11 (50)	Vehicle 4	Compartment 2		
	Load 11 (49,8)	Vehicle 4	Compartment 3		
	Load 15 (56,7)	Vehicle 1	Compartment 2		

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6. Conclusions

Genetic Algorithms is an approximate solution method that is considered as a flexible tool to solve optimization problems that present a considerable computational complexity. Load allocation problems, which are part of BBP problems, are categorized as NP-HARD complexity problems, meaning that mechanisms like Genetic Algorithms are required to provide workable solutions in a timely manner. The characteristics associated to selection, crossing and mutation operators offer advantages both in the diversification and in the intensification of the search space, which prevents the algorithm from being trapped in local optimum and can generate answers closer to the optimal solution of the problem without additional computational costs.

Based on the results obtained for the different instances and their respective comparison with the optimal solution offered by the GUSEK software, it's validated that the genetic algorithm developed in the present investigation is a viable metaheuristic for the solution of load assignment problems because the solutions offered by the algorithm do not present a percentage difference of more than 15%, in relation to the solution offered by GUSEK software. In addition to this, it's necessary to emphasize that when solving the instances raised by the software, a computational cost was generated superior to the presented one when implementing the algorithm developed in Visual Basic for Applications (VBA) of Excel.

References

Daza, J. M., Montoya, J. R. y Narducci, F. (2009). Resolución del problema de enrutamiento de Vehicle s con limitaciones de capacidad utilizando un procedimiento metaheurístico de dos fases. *Revista Escuela de Ingenierías de Antioquia (EIA), 12, 23-38.*

Delorme, M., Iori, M. y Martello, S. (2016). Bin packing and cutting stock problems: Mathematical models and exact algorithms. *European Journal of Operational Research, 255, 1-20.* doi: 10.1016/j.ejor.2016.04.030

Brandão, F. y Pedroso, J. P. (2015). Bin packing and related problems: General arc-flow formulation with graph compression. *Computers & Operations Research, 69, 56-67.* doi: 10.1016/j.cor.2015.11.009

Al-Hajri, M. T., Abido, M.A. y Darwish, M.K. (2015). Assessment of genetic algorithm selection, crossover and mutation techniques in power loss optimization for a hydrocarbon facility. *Power Engineering Conference (UPEC), 2015 50th International Universities.*

Díaz, B., Pinto, D. y Von Lücken, C. (2013). Robust Network Design under Uncertain Taffic an approach based on Genetic Algorithm. *2013 XXXIX Latin American Computing Conference (CLEI)*

Hasancebi, O y Erbatur, F. (2000). Evaluation of crossover techniques in genetic algorithm based optimum structural design. *Computers and Structure,* 78(1-3), 435-448.

Javadi, AA., Farmani, R y T.P. Tan, T.P. (2005). A hybrid intelligent genetic algorithm. *Advanced Engineering informatics*, 19 (4), 255-262.

Alayande, A.S., Jimoh, A.A., Yusuff, A.A. y Awosope, C.O.A. (2015). Inherent Structural Characteristics Based Approach for Solving Generation-Load Allocation Problems. *IEEE AFRICON.* doi: 10.1109/AFRICON.2015.7331946

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Wei-long, Y. y Qing, L. (2007) Solving the Stochastic Location-Routing Problem with Genetic Algorith. *International Conference on Management Science & Engineering (14th)*, 429-434.

Sharifi, F, Fang, L y Afshar, A. (2010). A Negotiation Based Approach to Waste Load Allocation Problems. *International Conference on Systems, Man and Cybernetics (SMC),* 3022-3027. doi: 10.1109/ICSMS.2010.5641691

Gargiulo, F y Quagliarella, D. (2012). Genetic Algorithms fot the Resourse Constrained Project Scheduling Problem. *International Symposium on Computational Intelligence and Informatics,* 39-47. doi: 10.1109/CINTI.2012.6496807

Khelifi, M., Saidi, M. and Boudjit, S. (2016) Genetic algorithm based model for capacitated network design problem. *2016 24th International Conference on Software, Telecommunications and Computer Networks (SoftCOM)*

Kim, J. y Asce, M. (2012) Hybrid Genetic Algorithm Parameter effects for Optimization of construction resource allocation problem. *Construction Research Congress. ASCE 2012,* 1560-1569.

Miller, B.L. y Goldberg, D.E (1995) Genetic Algorithms, Tournament Selection, and the Effects of Noise. *IlliGAL Report No 95006. Department of General Engineering,University of Illinois at Urbana-Champaign.*

Pan That Pann Phyu, S. y Srijuntongsiri, G. (2016), Effect of the number of parents on the performance of multi-parent genetic algorithm. *Knowledge, Information and Creativity Support Systems (KICSS), 2016 11th International Conference on*

Renner, G. y Ekárt, A. (2003). Genetic algorithms in computer aided design. *Computer-Aided Design*, 35 (5), 461-476.

Roeva, O. y Fidanova, S. (2013) Algorithm Performance in Case of Cultivation Process Modelling. *Proceedings of the 2013 Federated Conference on Computer Science and Information Systems*, 371-376.

Biography

Natalia Alejandra Gelves Tello Industrial Engineer from the Industrial University of Santander, Bucaramanga, 2015. Candidate for the Master of Industrial Engineering from the Pontifical Universidad Javeriana, Bogotá. Co-author of 1 indexed article in Publindex (Category A2). Knowledge in the management of programming languages like MATHPROG, C ++, VBA, MATLAB. High investigative interest in the optimization of the processes associated with logistics and production.

Mónica Patricia Acosta Rodríguez Industrial Engineer from El Bosque University, Bogotá, 2012. Candidate for the Master's Degree in Industrial Engineering from Pontifical Universidad Javeriana, Bogotá. Experienced in issues of process improvement, BPM, BPMS, ITIL, marketing and sales of different organizations in the services and manufacturing sector. High interest in issues of improvement and optimization of processes in the different applicable areas.

Juan Pablo Caballero Villalobos: Industrial Engineer from Pontifical Universidad Javeriana, 1999. Master's degree in Industrial Engineering, Andes University, 2005. PhD in Engineering from Andes University, 2016. Professor at Pontifical Universidad Javeriana and currently Director of Master's in Industrial Engineering of the Pontifical Universidad Javeriana. High interest in production and logistics.

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ANNEX 1:

Instance P.

Vehicle	Compartment	Load	Categories
v1	c1	f1	s1
v2	c2	f2	s2
v3	c3	f3	s3

Volume capacity of vehicle compartments			
	c1	c2	c3
v1	20	15	30
v2	18	17.5	25
v3	22	20	30
Weight capacity of vehicle compartments			
	c1	c2	c3
v1	210	180	390
v2	188	175	280
v3	221	210	301
Fixed cost for transporting loads			
	v1	v2	v3
f1	20	25	21
f2	18	17.5	20
f3	22	20	21
Constraint of transport of loads in the same compartment			
	f1	f2	f3
f1	1	1	0
f2	1	1	1
f3	0	1	1
Constraint of transporting loads in the same vehicle-different compartment			
	f1	f2	f3
f1	0	0	55
f2	0	0	0
f3	55	0	0
Constraint of carrying loads on the same vehicle-any compartment			
	f1	f2	f3
f1	0	1	0
f2	1	0	0
f3	0	0	0
Category of vehicles			
	s1	s2	s3
v1	1	1	0
v2	1	0	1

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v3	1	1	1
Maximum number of vehicles to be used by category			
1			

Density of loads	
f1	1.23
f2	10
f3	4.5
Supply of loads	
f1	1200
f2	570
f3	887
Profit of loads	
f1	20
f2	31
f3	21.8

Instance G.

Vehicle	Compartment	Load	Categories
v1	c1	f1	s1
v2	c2	f2	s2
v3	c3	f3	s3
v4		f4	s4
v5		f5	s5
v6		f6	
v7		f7	
v8		f8	
v9		f9	
v10		f10	
v11		f11	
v12		f12	
v13		f13	
v14		f14	
v15		f15	

Volume capacity of vehicle compartments			
	c1	c2	c3
v1	21	16	21
v2	21	15	17
v3	16	23	16
v4	18	21	15
v5	22	19	17

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v6	17	25	25
v7	23	25	25
v8	16	24	19
v9	22	20	17
v10	20	23	19
v11	17	25	21
v12	23	24	20
v13	17	17	19
v14	17	20	21
v15	16	22	17
Weight capacity of vehicle compartments			
	c1	c2	c3
v1	268	300	289
v2	299	293	295
v3	226	282	239
v4	251	283	293
v5	249	294	257
v6	238	281	230
v7	264	250	296
v8	231	260	241
v9	293	232	266
v10	250	259	300
v11	291	292	282
v12	241	232	279
v13	250	275	258
v14	263	290	282
v15	298	279	237

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Fixed cost for transporting loads															
	v1	v2	v3	v4	v5	v6	v7	v8	v9	v10	v11	v12	v13	v14	v15
f1	130.8	363.1	261.5	136.2	602.3	474.6	473.1	143.1	173.1	396.9	500	160	523.8	432.3	282.3
f2	420.8	262.3	232.3	463.1	199.2	470	596.9	333.1	505.4	199.2	500.8	339.2	490	506.9	428.5
f3	249.2	566.2	535.4	571.5	378.5	136.9	404.6	546.9	276.9	306.9	290.8	403.8	567.7	487.7	450.8
f4	287.7	176.2	419.2	386.2	509.2	340.8	456.9	510.8	565.4	374.6	513.8	580	304.6	318.5	577.7
f5	381.5	341.5	179.2	481.5	157.7	168.5	213.1	609.2	369.2	256.9	322.3	363.1	210.8	416.2	609.2
f6	314.6	5438	346.9	602.3	280.8	442.3	435.4	342.3	353.8	415.4	613.1	203.1	364.6	236.9	270
f7	546.9	317.7	239.2	391.5	550.8	499.2	415.4	354.6	297.7	317.7	140	350	130.8	453.8	494.6
f8	206.9	593.8	459.2	301.5	546.2	494.6	176.9	363.1	530.8	223.8	140	445.4	320	580	312.3
f9	273.8	593.8	160.8	129.2	153.1	142.3	523.8	376.9	320	256.9	444.6	370	475.4	154.6	243.1
f10	325.4	577.7	272.3	528.5	380.8	529.2	243.8	496.2	201.5	288.5	226.9	386.2	130.8	516.9	347.7
f11	460.8	608.5	152.3	204.6	123.1	350	453.1	400	166.2	440	565.4	160	279.2	609.2	222.3
f12	530	304.6	116.9	273.1	253.1	289.2	209.2	553.1	322.3	325.4	318.5	558.5	400.8	463.1	126.9
f13	603.8	466.9	318.5	188.5	473.1	416.9	489.2	295.4	229.2	143.1	270.8	334.6	133.1	286.2	296.9
f14	430	396.2	571.5	346.9	597.7	384.6	490	305.4	447.7	280.8	326.9	205.4	219.2	536.2	282.3
f15	280	346.2	549.2	426.9	608.5	281.5	286.2	563.1	136.2	519.2	506.9	381.5	229.2	239.2	361.5

Constraint of transport of loads in the same compartment			
	f1	f2	f3
f1	1	1	0
f2	1	1	1
f3	0	1	1

Constraint of transporting loads in the same vehicle-different compartment			
	f1	f2	f3
f1	0	0	55
f2	0	0	0
f3	55	0	0

Constraint of carrying loads on the same vehicle-any compartment			
	f1	f2	f3
f1	0	1	0
f2	1	0	0
f3	0	0	0

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Category of vehicles					
	s1	s2	s3	s4	s5
v1	0	1	1	0	0
v2	0	0	0	1	1
v3	1	0	0	0	1
v4	1	0	0	0	0
v5	1	1	1	1	1
v6	1	1	1	0	1
v7	0	1	1	1	0
v8	0	1	0	1	1
v9	1	1	0	0	1
v10	0	1	1	0	1
v11	1	0	1	1	1
v12	1	0	1	1	0
v13	0	1	1	0	1
v14	0	1	1	1	1
v15	0	0	1	0	1
Maximum number of vehicles to be used by category					
1					

Density of loads	
f1	1.667
f2	2.667
f3	2.667
f4	3
f5	2.667
f6	3
f7	3
f8	3.333
f9	2
f10	3
f11	3.333
f12	1.667
f13	2.333
f14	3
f15	3.333
Supply of loads	
f1	1906
f2	2967
f3	2448
f4	4338
f5	2498
f6	1475
f7	4161
f8	3662
f9	1039
f10	3080
f11	3568
f12	3616
f13	390
f14	4696
f15	370
Profit of loads	
f1	29
f2	22
f3	30
f4	23
f5	30
f6	29
f7	22
f8	20
f9	29
f10	27
f11	27
f12	21
f13	20
f14	21
f15	25

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