

A hybrid heuristic approach for the multi-objective multi depot vehicle routing problem

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ABSTRACT

Efficiency in logistics is often affected by the fair distribution of the customers along the routes and the available depots for goods delivery. From this perspective, in this study, the Multi-depot Vehicle Routing Problem (MDVRP), by considering two objectives, is addressed. The two objectives in conflict for MDVRP are the distance traveled by vehicles and the standard deviation of the routes' length. A significant standard deviation value provides a small distance traveled by vehicles, translated into unbalanced routes. We have used a weighted average objective function involving the two objectives. A Variable Neighborhood Search algorithm within a Chu-Beasley Genetic Algorithm has been proposed to solve the problem. For decision-making purposes, several values are chosen for the weight factors multiplying the terms at the objective function to build up a non-dominated front of solutions. The methodology is tested in large-size instances for the MDVRP, reporting noticeable results for managerial insights.

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1. Introduction

One of the functions of logistics companies is to implement and control the movement of goods from points of origin to customers' locations within the supply chain, considering efficient and cost-effective operations in their fleet. In the academic environment, a mathematical representation of the goods transport in a logistics company is provided by the Vehicle Routing Problem (VRP) and its variants, which includes the minimization of the total distance traversed by a fleet of vehicles to meet the demand of geographically dispersed customers, subject to operational constraints. Involved in the VRP framework, the Multi-Depot Vehicle Routing Problem (MDVRP) corresponds to an essential and challenging approach in logistics management that has been considered mainly during the last decade by researchers and practitioners (Jayarathna et al., 2021; Karakatič & Podgorelec, 2015; Jayarathna et al., 2020). According to the MDVRP dynamics, several depots are presented from which the vehicles start and end their respective routes, delivering the demand to the customers that are spatially distributed. Each route is assigned to the same depot, and each customer must be visited only once.

The MDVRP is a variant of the VRP considered within the NP-hard optimization problems and, therefore, computationally hard to solve. Due to the combinatorial explosion, exact algorithms are not a proper alternative to obtain an optimal or at least a good quality solution for the MDVRP, particularly for large-size instances (Zacharia et al., 2021). Conversely, in real-world applications and academic studies, there have been aspects of equity and fairness related to balancing resources. Although more expensive, balanced routes in the MDVRP follow better exploitation of resources and equilibrium in the workload distribution. Additionally, a higher level of customer satisfaction can be obtained with improved decisions of routing and scheduling based on balancing, which results in more customers being served promptly (Ho et al., 2008). Additionally, the unbalanced routes represent the least expensive solutions, inefficient when considering the incomplete usage of available

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resources, such as vehicle capacity. Non-monetary benefits, i.e., employee satisfaction, increment in customer service, and flexible resource availability, follow equity in resource utilization and a fair workload distribution (Mancini et al., 2021). The contributions of this study are listed as follows, combining practical approaches found so far in the MDVRP subject:

- A hybrid methodology between metaheuristic techniques using a VNS algorithm embedded in a CBGA is implemented, which has reported good performance and results in other MDVRP works-related.
- Two objectives under conflict are considered in the objective function: distance traveled and route balancing. The route balancing is calculated in terms of the standard deviation of the length of the routes.
- For route balancing, instead of the traditional difference between the longest and the shortest route, we use the standard deviation of the length of the routes, which is an effective measurement index to describe the level of parity in a routing solution. A more significant standard deviation indicates unbalanced routes.
- For decision-making purposes, we present the results in terms of a non-dominated front of solutions.

The remainder of this paper is organized as follows: Section 2 describes a review of the literature around the MDVRP; Section 3 explains the MDVRP mathematical model considering the distance traveled and route balancing terms; in Section 4, the hybrid methodology between the Chu-Beasley Genetic Algorithm and the Variable Neighborhood Search is proposed. Section 5 depicts the experimental results of the proposed methodology. Finally, Section 6 presents the concluding remarks and avenues of research.

2. Literature review

In the specialized literature, the theoretical research around the MDVRP is abundant, showing a variant of the VRP that is widely related to a real-life application where the logistic companies account for not only one depot but several depots to deliver the goods and meet the customers' demand. According to the systematic survey performed in (Karakatić & Podgorelec, 2015), several GA approaches can be identified, with different versions for the genetic operators. The tournament/linear-ranking selection, crossover, and exchange mutation are implemented for the benchmark instances for comparison purposes. Our review has targeted the heuristics and meta-heuristics algorithms used for solving the MDVRP, emphasizing the genetic algorithm GA, the Variable Neighborhood Search VNS algorithm, and the hybrid techniques, preserving a chronological order.

Early contributions are identified that utilize different ways to solve the MDVRP. In Chao et al. (2013), high-quality routes are obtained when the assignment of customers is used prior to the application of the heuristic. Although the heuristic is not referred with one of the current techniques used to solve the MDVRP, the authors explain it considering a two-phase heuristic: In the first step, the customers are assigned to each depot, then in the second step, the traditional CVRP is solved for each depot. Following the timeline and a similar approach as presented in Chao et al. (2012), the authors of Renaud et al. (1996) develop a Tabu Search for the MDVRP considering the intensification and diversification strategies to increase the likelihood of moving out from a local optimum, which is often an issue when solving NP-hard problems with meta-heuristic techniques. Genetic algorithms are also found in the early research around the MDVRP as an alternative to providing high-quality solutions within reasonable computational time by using different types of selection, crossover and mutation operators, and diverse chromosomes for the problem representation (Skok et al., 2020). Similarly, the efforts performed in (Filipec et al., 2000) are focused on reducing the search space domain for rapid convergence with a heuristic technique applied in the population initialization and over the genetic operators. Later, some references show strategies in the mutation stage, such as inter-depot exchanging provided by (Ombuki-Berman & Hanshar, 2009), resulting in competition for the MDVRP and an indirect encoding that remains flexible in the algorithm when other objectives and constraints are added.

The research in (Surekha & Sumathi, 2011) develops an assignment of each customer to the nearest depot before applying the Clark and Wright algorithm to improve the initial solution for the GA. In the same manner, Yücenur and Çetin (2011) studied the performance clustering combined with the application of the genetic operators when solving the MDVRP, with considerably less computational time. Other practices in the framework of "cluster first then route" are found in (Geetha, Vanathi, & Poonthilir, 2012), which presents a hybrid methodology between the GA and the particle swarm optimization PSO algorithm, including a hybrid PSO algorithm that comprises k-means clustering and customers exchange between routes. This approach is used in delivering pharmacy programs and waste collection. Unlike the traditional techniques Li et al. (2012) and (Luo & Chen, 2014) propose a novel optimization method population-based known as Shuffled Frog Leaping Algorithm SFLA for the MDVRP. This approach is based on the memetic evolution of a group of frogs seeking the place with the maximum amount of food. On the other side, a hybrid granular tabu search algorithm is applied to the MDVRP and introduced by Escobar et al. (2014) based on previous research on the capacitated location routing problem. This approach presents a perturbation procedure to escape from the local optimum using different diversification strategies and local movements.

Hybrid methodologies are also found in (Liu, Jiang, & Geng, 2014) and (Mirabi, 2014) performing within the GA, improvement strategies in the individual before introducing it in the current population, and employing the electromagnetism algorithm. This algorithm is based on the attraction-repulsion principle of the electromagnetism theory, where electrically charged particles are considered the population spread in the solution space. A decomposition approach is proposed in (de

Oliveira et al., 2016) for a parallel environment. For this work, the general problem is split into several subproblems that evolve independently. Each subproblem corresponds to a CVRP where a unique depot attends to all the customers. Unlike other studies that opt for clustering and routing, the research in (Singh et al., 2021) highlights that both stages should be done as a joint exercise to ensure the optimal solution. In this regard, different versions of GA are implemented, differing in the following crossover operators: single point, cyclic and uniformed ordered crossover. Likewise, in (Prabu, Ravisasthri, Sriram, & Malarvizhi, 2019), a population initialization strategy for the GA is proposed that generates a special population featured by quality, randomness, and diversity. A different technique is addressed in (Li et al., 2019b) for the MDVRP, using an improved ant colony optimization algorithm that involves an innovative approach for obtaining a better solution with pheromone updating. In this case, the MDVRP introduces the environmental component, minimizing travel time and emissions while maximizing profit. Correspondingly, in (Li et al., 2019) it is shown a similar work as presented in (Li et al., 2019b), considering the time windows constraints and an initial stage of the k-means clustering algorithm to decompose the problem into several subproblems to reduce the complexity in the solving procedure.

Recent contributions in the MDVRP are found to be applied for carbon emissions, time-dependent networks, hazardous materials transportation, waste collection, and food distribution. In (Zhang et al., 2020) is presented a variant of the MDVRP named multi-depot green vehicle routing problem MDGRP, in which the vehicles must refuel in the alternative fuel stations during the service process, and the objective function corresponds to the minimization of the carbon emissions. It uses a Partition-based algorithm and a two-stage methodology based on an ant colony algorithm to solve the problem. Hybrid methodologies are often used, such as Hou et al. (2021) and Hou et al. (2021), where the GA works together with the Variable Neighborhood Search Algorithm VNS to provide rapid convergence. The initial solution is generated through a clustering process that considers the spatial-temporal parameter of the customer respect with the depot. Other hybrid approaches are presented in (Zhou et al., 2021; Yu et al., 2022). The proposal in Zhou et al. (2021) deals with the conflict between two objectives: the risk and cost of transportation. The result comprises a set of Pareto optimal solutions that are provided using the GA with the ϵ -constraint method. Similarly, Yu et al. (2022) and Moonsri et al. (2021) described a combined approach with genetic algorithms that work in conjunction with simulated annealing; and a hybrid differential evolution algorithm to solve the MDVRP considering a heterogeneous fleet vehicle, time windows, and inventory constraints.

Unlike the works reported in the literature, our study tackles the MDVRP with an embedded framework of the VNS algorithm in the CBGA instead of using the two-phase methodologies that are commonly used (Geetha et al., 2012; Shen et al., 2018; Zhang et al., 2020). Compared with Hou et al. (2021) and Dengkai et al. (2021), in this study, the VNS uses six different neighborhood structures, some of which involve two routes from the individual by using swapping and insertion operators. Mainly, the neighborhood structures Intra-insertion, Intra-swap, Inter-insertion, and Inter-swap are used in our proposal to refine the local search, and the structures Intra-2opt and Inter-2opt are employed for search diversification and escape from the local optima trap (Peng et al., 2020). Additional to the research performed from the route balancing perspective for the traditional vehicle routing problem, in this study, the workload distribution is considered by using the standard deviation of the length of the routes applied for the MDVRP, which has a different connotation since the routes are in most of the cases, served by different depots. According to Matl and Hartl (2017), the standard deviation for route balancing is likely the most well-known statistical measure for dispersion, compared with other measures in the route balancing context, such as the min-max approach, lexicographic mi-max, the difference between the largest and shortest routes and, the mean absolute deviation.

3. Mathematical formulation of the MDVRP with route balancing

The MDVRP is an extension of the CVRP where more than one depot is considered, seeking optimal routes with minimum traveled distance. Additionally, the vehicle must start and end at the same depot. The maximum number of vehicles per depot is provided as input data (Subramanian, Ucho, & Satoru, 2013), so it can be suitable to know the minimum of vehicles needed to meet the customer's demand to reduce the search space in the solution method. Additionally, the location of the customers and depots is known, the fleet of vehicles is limited and homogeneous, i.e., the cargo capacity is the same for all the vehicles, and the customer's demand is deterministic (Tang et al., 2016).

Mathematically, the MDVPR is defined by a complete graph $G = (V, A)$ where $V = \{1, \dots, n + w\}$ is the set of vertices and $A = \{(i, j): i, j \in V, i \neq j\}$ is the set of arcs. The set of vertices V is split into two subsets: $V_c = \{1, \dots, n\}$ and $V_d = \{n + 1, \dots, n + w\}$ representing the sets of customers and depots, respectively. Each depot has a maximum number of available vehicles with maximum load capacity, belonging to set K . A non-negative demand d_i is associated for each vertex i belonging to the set of customers V_c . A distance matrix $dist_{i,j}$ related to the set of arcs A is necessary to quantify the objective function, that is, in terms of the total distance traveled by the fleet of vehicles. In the MDVRP, the performed routes are obtained at minimum cost in such a way that: each route starts and ends in the same depot, each customer is visited by just one vehicle, and the route demand cannot exceed the vehicle capacity.

Nomenclature

Sets:

V_c Customer nodes

V_d	Depot nodes
V	Customers and depots $V = V_c \cup V_d$
K	Vehicles

Parameters:

$dist_{ij}$	Distance between nodes i and j
Q_k	Load capacity of the vehicle k
dep_start	Vector of depot nodes
dep_end	Copy vector of depot nodes
α	Weight factor for the traveled distance term in the objective function
β	Weight factor for the standard deviation term in the objective function

Variables:

x_{ijk}	Binary decision variable that takes the value of 1 if vehicle k goes from node i to node j and 0 otherwise
Y_{ik}	Binary decision variable that takes the value of 1 if customer at node i is visited by vehicle k
d_i	Demand at node i
t_{ijk}	Remaining merchandise to be delivered at arc i, j by vehicle k

The first objective function represents the minimization of costs presented as follows:

$$\min Z = \sum_i \sum_j \sum_k dist_{ij} \cdot x_{ijk} \quad (1)$$

On the other hand, route balancing is also introduced in the MDVRP mathematical representation, providing the multi-objective approach for this research. In the field of route balancing, some of the references reviewed tackle this area using multi-objective approaches, considering the minimization of both: the distance traveled by vehicles and the most extended route length and the shortest route length (Jozefowicz et al., 2007, 2009; Borgulya, 2008). Other objectives related to route balancing are framed within the number of customers visited per route, the time required to perform the route, and the waiting/delayed time of the route (Zhou et al., 2013). Although route balancing can also be associated with variables such as time and demand per customer, in most cases, the route length is the dominant approach for route balancing, as this represents a variable that contributes to a fairer workload distribution over the routes. Consequently, the number of customers at each route is balanced since the customers are uniformly distributed in the space. In this sense, according to (Galindres, Toro, & Gallego, 2018), the route balancing index length-related can be effectively measured by the standard deviation SD of the length of the routes, i.e., second objective function, as shown in Equation (2):

$$SD = \sqrt{\sum_{r \in T} (l_r - \mu) / |T|} \quad (2)$$

Being l_r the route length belonging to the set of routes T , μ the average of the length of the routes in the solution, and $|T|$ the number of routes. Accordingly, the general objective function is described by Eq. (3), considering the minimization of the distance (1) and the route balancing (2).

$$\min Z = \alpha \sum_i \sum_j \sum_k dist_{ij} \cdot x_{ijk} + \beta \sqrt{\sum_{r \in T} (l_r - \mu) / |T|} \quad (3)$$

The first term of Equation (3) corresponds to (1) multiplied by a factor α , and the second term corresponds to (2) multiplied by a factor β . Note that both terms are affected by the weight factors that provide dominance over each objective.

subject to:

$$\sum_k Y_{ik} = 1 \quad \forall i \in V_c \quad (4)$$

$$\sum_{j \in V_c} x_{ijk} = Y_{ik} \quad \forall i \in V_c, k \in K \quad (5)$$

$$\sum_{i \in V_c} \sum_{k \in K} x_{ijk} = 1 \quad \forall j \in V_c, i \neq j \quad (6)$$

$$\sum_{i \in V_c} x_{ihk} - \sum_{j \in V_c} x_{hjk} = 0 \quad \forall h \in V, k \in K \quad (7)$$

$$\sum_{i \in V_c} \sum_{j \in V} d_i \cdot x_{ijk} \leq Q_k \quad \forall k \in K \quad (8)$$

$$\sum_{j \in V_c} x_{ijk} \leq 1 \quad \begin{array}{l} \forall i \in V_d \\ i \in dep_{start}(k), k \in K \end{array} \quad (9)$$

$$\sum_{i \in V_c} x_{ijk} \leq 1 \quad \begin{array}{l} \forall j \in V_d \\ j \in dep_{end}(k), k \in K \end{array} \quad (10)$$

$$\sum_{i \in V} x_{jik} = 0 \quad \begin{array}{l} \forall j \in V_d \\ j \notin dep_{start}(k), k \in K \end{array} \quad (11)$$

$$\sum_{j \in V} x_{jik} = 0 \quad \begin{array}{l} \forall i \in V_d \\ i \notin dep_{end}(k), k \in K \end{array} \quad (12)$$

$$\sum_{i \in dep_{start}(k)} \sum_{h \in V_c} x_{ihk} - \sum_{h \in V_c} \sum_{j \in dep_{end}(k)} x_{hjk} = 0 \quad \forall k \in K \quad (13)$$

$$\sum_{\substack{j \in V \\ j \neq q}} t_{qjk} \leq \sum_{\substack{i \in V \\ i \neq q}} [t_{iqk} - dist_{iq} \cdot x_{iqk}] + Q \cdot \left[1 - \sum_{\substack{i \in V \\ i \neq q}} x_{iqk} \right] \quad \begin{array}{l} \forall q \in V_c \\ \forall k \in K \end{array} \quad (14)$$

$$t_{iqk} \geq 0 \quad \begin{array}{l} \forall i \in V \\ \forall q \in V \\ i \neq q \\ \forall k \in K \end{array} \quad (15)$$

$$t_{iqk} \leq Q \cdot x_{iqk} \quad \begin{array}{l} \forall i \in V \\ \forall q \in V \\ i \neq q \\ \forall k \in K \end{array} \quad (16)$$

$$\sum_{\substack{i \in V_d \\ i = dep_{start}(k)}} \sum_{q \in V_c} t_{iqk} \leq \sum_{i \in V_c} d_i \quad \forall k \in K \quad (17)$$

Expressions (4) and (5) guarantee that each customer is visited by one vehicle. In Eq. (6), the number of arcs entering a customer node is equivalent to one. Eq. (7) assure that the number of arcs entering a node equals the number of arcs leaving the same node, either a customer or a depot. Expressions in (8) establish that the sum of the customers' demands belonging to a route must be less than the load capacity of the vehicle visiting such route. Eq. (9) and Eq. (10) ensure that a vehicle returns

to the same depot if it leaves a determined depot. Conversely, Eq. (11) and Eq. (12) avoid the vehicles arriving at a different depot from which they depart. Eq. (13) guarantees that the number of arcs leaving and entering a depot node are equal. Expressions (14) to (16) are for subtours elimination purposes, tracking the merchandise flow through the arcs of the route. Lastly, Eq. (17) assures that the total demand of the customers is greater or equal to the sum of the flow through the arcs.

4. Proposed solution algorithm: CBGA-VNS

Due to the NP-hard nature, the mathematical model of the MDVRP with route balancing presented in Section 3 is solved by using a hybrid methodology based on the Variable Neighborhood Search VNS algorithm embedded in the Chu-Beasley Genetic Algorithm CBGA, named in this work as CBGA-VNS. In particular, this combination of metaheuristic techniques provides the ability to escape from local optima and converge rapidly to a high-quality feasible solution. The computational flow of the combined CBGA-VNS is presented in Fig. 1.

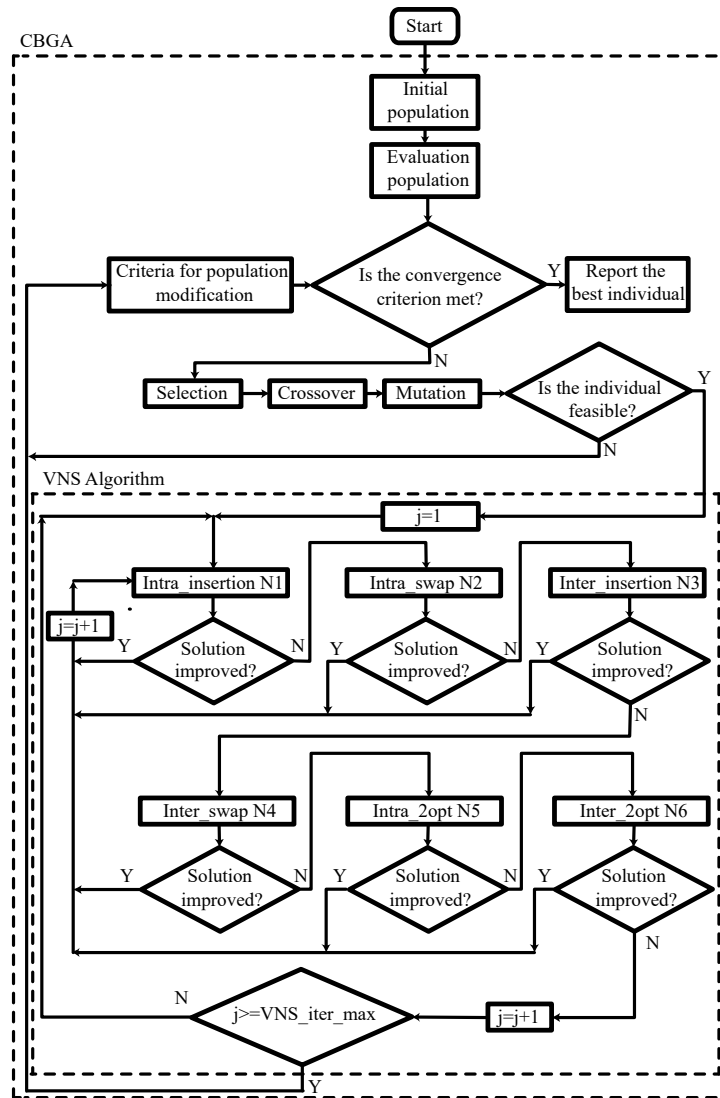


Fig. 1. CBGA-VNS computational flow to solve the MDVRP

As presented in Fig. 1, the initial population of individuals is randomly generated with the subsequent evaluation of the objective function (3). If the convergence criterion is met, the best individual is reported. Otherwise, it is proceeded with the genetic operators of selection, crossover, and mutation belonging to the GA. Although the GA is characterized as robust, of high parallelism, and has strong search ability, the convergence speed is slow and tends to fall into a local optimum. The VNS algorithm is performed with the corresponding neighborhood structures as long as the individual is a feasible solution before evaluating whether the individual can be introduced to the current population. The VNS algorithm has a strong local search capability, providing a means to escape from local optima and search over other regions of the solution space. A total of six neighborhood structures are embedded in the GA from N1 to N6. Each structure is executed over the individual to improve the objective function. The following neighborhood structure is executed if the objective function still needs to be improved.

Otherwise, the process returns to the first structure. Note that the VNS iteration increases when the solution is improved, and all structures are examined if the objective function (3) is not improved. This process is executed until a maximum of iterations of the VNS is reached. Later, the individual is introduced to the current population using the guidelines for population modification established in the CBGA until a convergence criterion has been complied. The neighborhood structures of the VNS algorithm and the CBGA operators in the context of the solution representation adopted for this problem are explained in further detail in the following subsections. Algorithm 1 describes the general procedure of the CBGA-VNS.

Algorithm 1. General procedure of the CBGA-VNS

1: **Input:**

2: *popsize*: Population size;

3: NI_{CBGA} : Maximum of iterations in the CBGA;

4: **Output:** Best individual S in the current population

5: $pop_{start} = [ind_1 \ ind_2 \ \dots \ ind_{popsize}]$; % Generate initial population

6: $Z_{fitness}(pop_{start})$; % Compute fitness function of individuals in pop_{start}

7: $pop_{curr} \leftarrow pop_{start}$;

8: **while** $i \leq popsize$

9: $[ind_a, ind_b] = selection(pop_{curr})$; % ind_a and ind_b result from the selection process

10: $ind_x = crossover(ind_a, ind_b)$; % ind_x results from crossing ind_a and ind_b

11: $ind_{mut} = mutation(ind_x)$; % ind_{mut} results from the mutation process of ind_x

12: **if** $infeas(ind_{mut}) = 0$ **then**

13: $S \leftarrow ind_{mut}$; % S is a feasible solution

14: $ind_{VNS} = VNS(S)$; % VNS algorithm is applied over feasible solution S

15: **else**

16: **go to 9**

17: **endif**

18: $pop_{new} = update(ind_{VNS}, pop_{curr})$; % Applying criteria to introduce ind_{VNS} in pop_{curr}

19: $pop_{curr} \leftarrow pop_{new}$;

20: $incumb = \min(Z_{fitness}(pop_{curr}))$; % Computation of incumbent

20: **endwhile**

21: **Return** $incumb$

4.1. Chu-Beasley Genetic Algorithm CBGA

A genetic algorithm is a metaheuristic technique based on the evolution of the species, framed within the survival capability of the most robust population over time. As the species evolve, better individuals with improved features are introduced into the current population. Continuous and discrete optimization problems can be solved by using the intelligent probabilistic search attributed to the genetic algorithm, using three basic rules of evolution, namely genetic operators: selection, crossover, and mutation (Montoya, Gil-González, & Orozco-Henao, 2020). These rules are applied to each generation of individuals evaluated by a fitness measure comprising the value of (3) and infeasibility. The CBGA was initially designed to solve the generalized assignment problem (Chu & Beasley, 1997), with reports of its adjustment to other types of problems with

noticeable results. Unlike the traditional genetic algorithm, the CBGA presents features that make it competitive in solving large-size problems. According to population replacement criteria, only one individual is replaced in the generation.

The algorithm's performance to solve the MDVRP can be affected contingent upon the solution representation. The MDVRP solution or the chromosome is often represented by an array of stops describing the customers visited sequentially. This representation is depicted in Figure 2 and has been widely used by genetic algorithms researchers working on complex optimization problems (Skok et al., 2020). Fig. 2 describes an example of the chromosome representing the MDVRP solution, composed of thirteen customers and three depots. The array encompasses the routes one after the other, delimited by their respective depots.

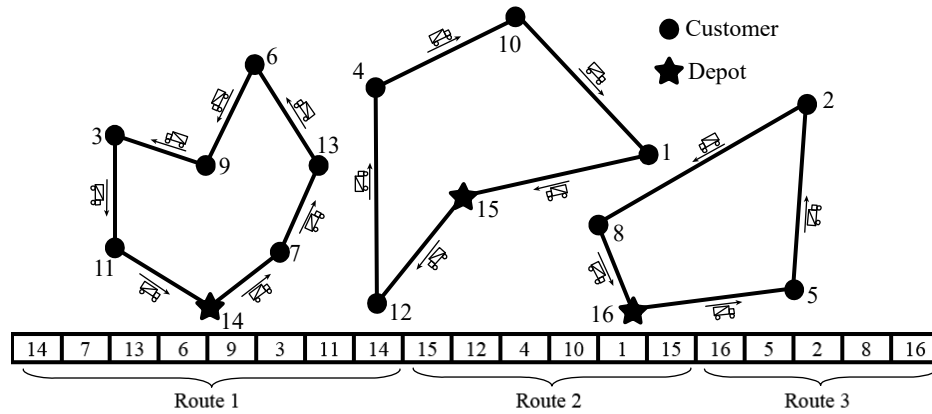


Fig. 2. Solution representation of the MDVRP

The constraints of the mathematical model presented in Eq. (3) to Eq. (17) warranty the feasibility of the individuals in the population. Fig. 3 presents an infeasible solution for a fleet of vehicles with a capacity of 150. Notice that Route 1 is not feasible because the vehicle cannot meet the total demand of the customers along the route, which is 175. Route 2 is a sub-tour, needing more depots. The travel performed by the vehicle in Route 3 needs to comply with the constraint that mandates starting and concluding the route in the same depot. For Route 5, although the vehicle starts and ends in the same depot, the route could be feasible as the vehicle visits the same customer twice.

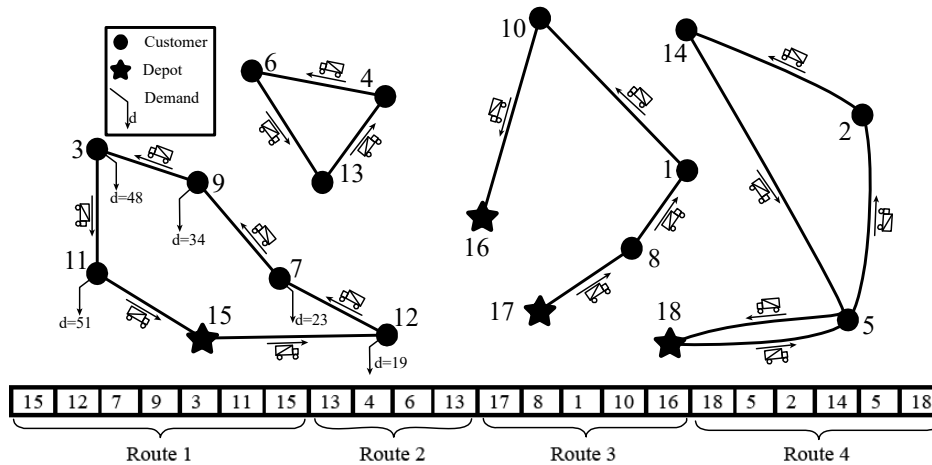


Fig. 3. Example of infeasible MDVRP solution. Vehicle capacity of 150

Feasibility is warranted by using the fitness function $Z_{fitness}$, which encompasses the objective function and the penalty terms related to the infeasibility in the constraints, as presented in Eq. (18).

$$Z_{fitness} = \alpha \sum_i \sum_j \sum_k dist_{ij} \cdot x_{ijk} + \beta \sqrt{\sum_{r \in T} (l_r - \mu) / |T| + Infeas} \tag{18}$$

Infeas1 and *Infeas2* are the penalty terms associated with: overload cargo capacity and routes starting and concluding in different depots, respectively. A descriptive representation of the fitness function computation is given in Algorithm 2. Subtours formation and customers visited more than once are avoided during the development of the genetic operators.

Algorithm 2. Computing fitness function for MDVRP solution

```

1: Input: Solution  $S, Q, d, dist_{ij}, \alpha, \beta$ 
2: Output: Fitness function  $Z_{fitness}$ 
3:  $0 \leftarrow d_{travel}$ 
4:  $0 \leftarrow Infeas$ 
5:  $r_1, \dots, r_T \leftarrow Routes\_extraction(S)$ 
6: for  $i = \{1, \dots, T\}$  do
7:    $l_{r_i} \leftarrow length(r_i)$  %Computation of length of route  $r_i$ 
8:    $d_{r_i} \leftarrow demand(r_i)$  %Computation of demand of route  $r_i$ 
9:    $0 \leftarrow Infeas1$  %Infeasibility due to not able to comply demand of route  $r_i$ 
10:   $0 \leftarrow Infeas2$  %Infeasibility due to start and end at different depots
11:  if  $demand(r_i) > Q$  then
12:     $Infeas1 \leftarrow BigM1 \cdot (demand(r_i) - Q)$ 
13:  endif
14:  if  $r_i(1) \neq r_i(end)$  then
15:     $Infeas2 \leftarrow BigM2 \cdot abs(r_i(end) - r_i(1)) \cdot l_{r_i}$ 
16:  endif
17:  $Infeas \leftarrow Infeas + Infeas1 + Infeas2$ 
18:  $d_{travel} \leftarrow d_{travel} + l_{r_i}$ 
19: endfor
20:  $STD \leftarrow Desv\_stand(r_1, \dots, r_T)$ 
21:  $Z_{fitness} \leftarrow \alpha \cdot d_{travel} + \beta \cdot STD + Infeas$ 
22: Return  $Z_{fitness}$ 

```

4.2. Initial population and genetic operators

This work adopts the standard practice for evolutionary algorithms, which includes randomly choosing the initial population to cover the entire search of space (Garcia-Najera & Bullinaria, 2011), despite the execution time for convergence is increased. With some knowledge about the MDVRP, by applying different heuristics for population initialization, the population can lead to a portion of the search space likely to provide local optimum solutions with a decreased execution time (Wink, Bäck, & Emmerich, 2012). The individuals can be feasible or infeasible due to the random nature of this initialization. They must differ from each other to warrant diversity, which must be warranted throughout the algorithm development. This set of solutions is likely to obtain some solutions with the same objective function. Furthermore, their codification must be different. Once the initial population is generated, the genetic operators of selection, crossover, and mutation are applied. Tournament selection is set for the MDVRP, considering two tournaments applied for the current generation of solutions. In each of them, k individuals of the current population are chosen to participate. The number of individuals k is usually chosen within 2 to 4. The process is as follows: k individuals of the current population are randomly chosen; their objective functions are compared, and the best fitness function is stored as the first parent. This process is repeated to find the second parent, considering that both parents must be different.

After selecting the two parents, the crossover operator is applied by interchanging their integer codifications in a one-point crossover process. This change results in two offspring, composed of a portion of the first parent's information and another portion of the information of the second parent. Only one offspring can pass to the next stage of the algorithm, which corresponds to mutation; the other offspring is randomly discarded. The point chosen for crossover must not correspond to a

depot for the first or the second parent. If the previous requirements are not in compliance with the crossover point, the resulting individuals could present routes with only one depot or no customers, which can perform issues in further algorithm steps. The resulting offspring may sometimes present different depots at the routes' beginning and end. This fact is translated into an infeasible solution penalized in its fitness function. For the example in Fig. 3, Fig. 4 shows the points along the chromosomes that are restricted for crossover points in grey.

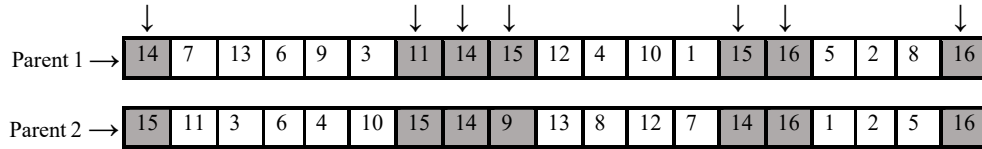


Fig. 4. Points that cannot be chosen for crossover

Once the crossover process is performed, the mutation is executed on the selected offspring. Before the mutation stage, it is checked if the offspring has repeated customers in its routes. Otherwise, the processes of selection and crossover are performed again until reaching offspring with different customers along the routes. The mutation stage involves the extraction of a random customer along one of the routes and inserting it into another randomly chosen route of the current offspring. This situation corresponds to a specific neighborhood structure used in the VNS algorithm, which is explained in more detail in the following section.

4.3. Variable Neighborhood Search VNS algorithm

After the mutation stage in the CBGA, a local refinement is implemented on the offspring previously introducing it into the population. This procedure is carried out by the Variable Neighborhood Search VNS algorithm, considering different neighborhood structures applied to the current offspring (Bo, Lifan, Yuxin, & Xiding, 2020). These VNS structures work randomly and correspond to the operators listed as follows:

Intra-insertion (N_1): One customer is chosen in the route and is relocated to the other two adjacent customers (Fig. 5).

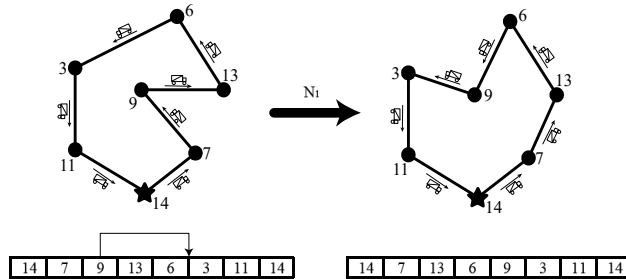


Fig. 5. Intra-insertion (N_1). Customer 5 is relocated within the customers 6 and 3.

Intra-swap (N_2): The position of two customers, not necessarily adjacent, is interchanged in the same route (Fig. 6).

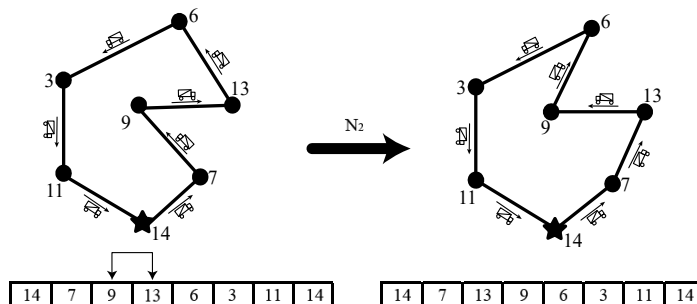


Fig. 6. Intra-swap (N_2). Customers 9 and 13 interchange of position in the same route.

Inter-insertion (N_3): Two routes are chosen from the current offspring. One of the customers of the first route is relocated within two adjacent customers in the second route (Fig. 7).

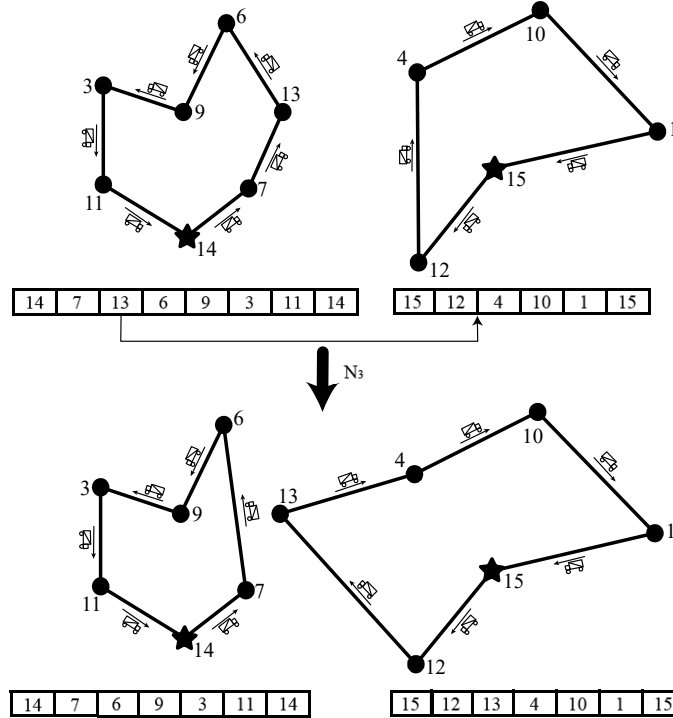


Fig. 7. Inter-insertion (N_3). Customer 13 from the first route is introduced within customers 12 and 4 of the second route.

Inter-swap (N_4): The location of two customers from two different routes is interchanged (Fig. 8).

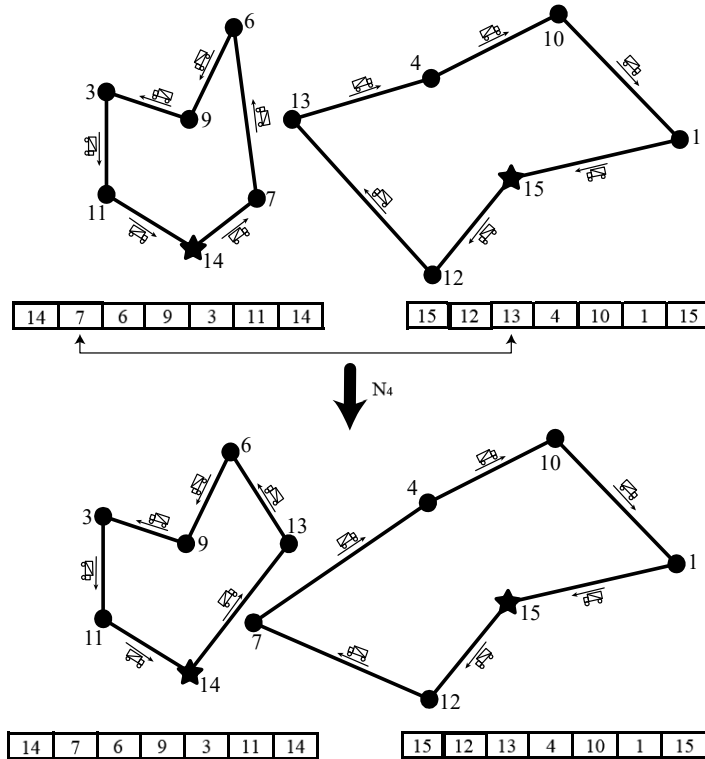


Fig. 8. Inter-swap (N_4). Customers 7 and 13 from different routes are interchanged.

Intra-2opt (N_5): One route is chosen from the current offspring. Then it is extracted a set of successive customers within two arcs. This set of customers is rearranged in inverse order. Subsequently, the resulting set is introduced again in the original arcs of the route (Fig. 9).

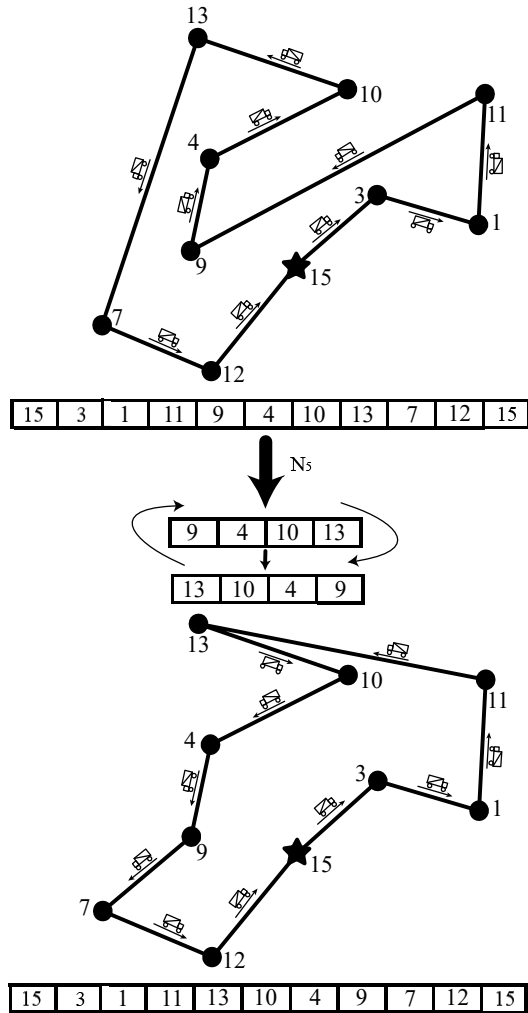


Fig. 9. Intra-2opt (N_5). The sequence of customers 9, 4, 10 and 13 is reversed.

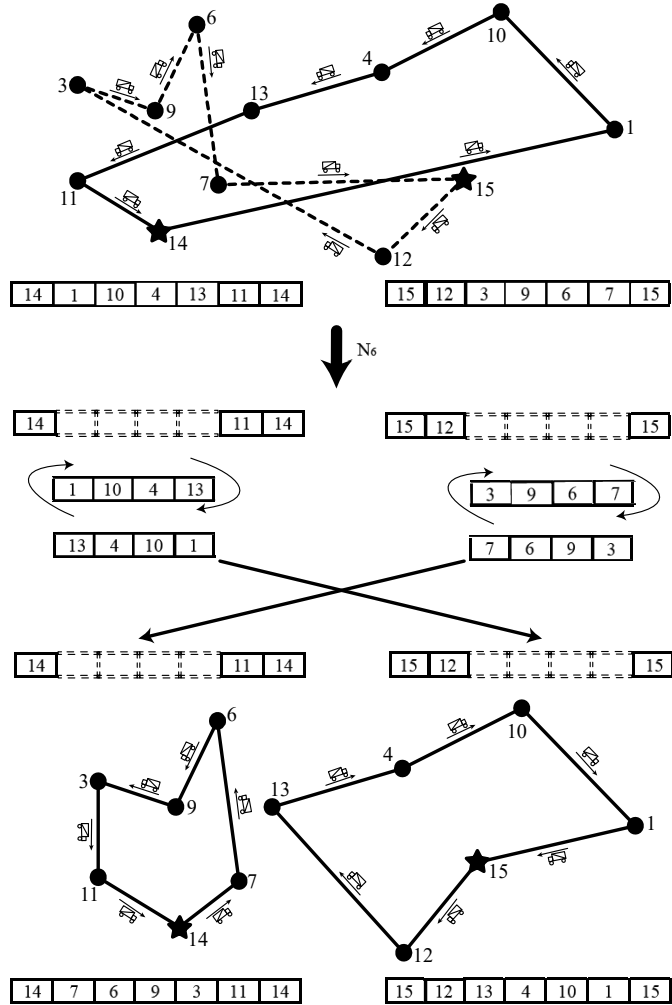


Fig. 10. Inter-2opt (N_6). Sequence of customers from two routes are swapped and interchanged between routes.

Inter-2opt (N_6): Two routes are chosen from the current offspring. The procedure performed is like operator N_5 , except that the resulting set of customers is introduced in the other route (Fig. 10). Following the flow diagram depicted in Fig. 1, a descriptive representation of the VNS is presented in Algorithm 3, considering a solution S as the input, and an improved S' as the output. Solution S' can also be a non-improved solution if none of the neighborhood structures could improve S .

Algorithm 3. Procedure of the VNS algorithm for a feasible solution S

- 1: **Input:** Feasible solution S , VNS_iter_max
 - 2: **Output:** Solution S'
 - 3: $1 \leftarrow j$;
 - 4: **while** $j \leq VNS_iter_max$ **do**
 - 5: **for** $n = \{1, \dots, NS\}$ **do** %Execute NS neighborhood structures
 - 6: $S' \leftarrow N_n(S)$; %Applying structure $N_n(S)$
 - 7: **if** $Z_{fitness}(S') < Z_{fitness}(S)$ **then**
 - 8: $j + 1 \leftarrow j$;
 - 9: $S' \leftarrow S$;
 - 10: **go to** 5 %If the solution is improved, the algorithm is executed again from N_1
 - 12: **endif**
 - 13: **endfor**
 - 14: $j + 1 \leftarrow j$;
 - 15: **endwhile**
 - 16: **Return** S'
-

5. Experimental results

The proposed CBGA-VNS is computationally tested in several MDVRP benchmark instances designed by Cordeau (Networking and Emerging Optimization, 2006), considering those arrangements with 48 to 144 customers and 2 to 8 vehicles per depot for demand compliance. The algorithm was executed on a computer cluster with two AMD Epyc 7702 processors and 64 cores per processor, and 256GB of RAM, and MATLAB R2022a. For decision-making purposes, the CBGA-VNS is run for different values of α and β , which are the factors affecting the terms of distance traveled and standard deviation, respectively, in the objective function. The standard deviation represents the unbalanced degree of the routes presented in the solution. Factor α is set from 1 to 0.8 in steps of 0.01, and factor β is set from 0 to 0.2 in steps of 0.01, conforming pairs of α and β values for each run. In total, the CBGA-VNS runs 20 times, providing twenty solutions, where each solution is composed of a distance traveled and a standard deviation of the routes presented in the solution. Factors α and β were chosen in such a way that the distance traveled be more important than the standard deviation in the objective function, to increase the likelihood to obtain the best-known-solution BKS concerning distance traveled. Since the BKS is less likely to obtain for values of α close to zero, in the experimental design we decided to run the methodology with $0.8 \leq \alpha \leq 1$. Once the solutions are provided, the dominance criteria (Deb et al., 2002) are performed to obtain a set of non-dominated solutions. The CBGA parameters are set in 20 individuals per generation, three individuals per tournament in the selection operation, and 65 thousand iterations for the stopping criteria. In the VNS, the parameter VNS_iter_max was set to 1000.

Table 1 shows the results for MDVRP instances P01 and P02, considering the non-dominated front of solutions. The first column is the MDVR instance, second and third columns are the distance traveled D_{trav} and standard deviation STD_{dev} of the routes, respectively. The fourth, fifth, and sixth columns are the best-known solution BKS from the literature, the difference in percent Gap [%] between the best solution of the front and the BKS, and the routes of the best solution in the front, respectively. P01 and P02 have the same number of customers and depots, including their coordinates, in these two instances. The difference stands in the number of vehicles per depot and merchandise capacity for the vehicle. Although the vehicle capacity is more significant in P02 than in P01, there are more vehicles available in P01, which provides better results in terms of GAP as the more significant number of vehicles available per depot, the more the options to provide a feasible and better-quality solution. It is necessary to point out that α and β values are not strictly directed with the distance traveled obtained. For α and β equal to 1 and 0 respectively, the distance traveled is not necessarily the smallest value in the front of solutions.

Table 1

Results for P01 and P02 MDVRP instances

Instance	α	β	D_{trav}	STD_{dev}	BKS	Gap [%]	Routes of the best solution
P01 Available vehicles: 4 No. customers: 50 No. of depots: 4 Capacity: 80	0,98	0,02	577,46	17,48	576,87	0,10	51-25-18-4-51
	0,8	0,2	580,71	16,51			54-29-2-16-50-21-54
	0,97	0,03	589,52	16,16			52-6-48-27-32-11-52
	0,86	0,14	592,79	15,63			54-20-3-36-35-54
	1	0	599,03	15,16			53-49-5-38-53
	0,93	0,07	599,38	13,81			53-9-34-30-39-10-53
	0,96	0,04	599,62	13,81			52-23-7-43-24-14-52
	0,83	0,17	599,62	13,81			51-17-37-15-33-45-44-51
	0,92	0,08	599,83	13,75			52-47-12-46-52
	0,9	0,1	599,83	13,75			52-1-22-28-31-26-8-52
0,91	0,09	602,55	13,01	51-13-41-40-19-42-51			
P02 Available vehicles: 2 No. customers: 50 No. of depots: 4 Capacity: 160	0,82	0,18	474,69	12,94	473,53	0,24	51-17-4-18-25-13-41-40-19-42-51
	0,97	0,03	488,42	8,54			52-6-23-7-43-24-14-47-12-46-52
	0,8	0,2	499,22	7,41			53-9-50-16-29-20-36-35-21-34-30-53
	0,89	0,11	503,32	4,68			53-38-11-5-37-44-15-45-33-39-10-49-53
	0,83	0,17	514,53	3,82			54-2-22-1-32-27-48-8-26-31-28-3-54

For a more significant number of customers, Table 2 presents the results for the instances P04, P05, and P07, composed of 100 customers with some differences in other parameters. The spatial distribution of the customers is the same for the three instances. In the second and third columns, the values in bold correspond to the best solution found, belonging to the non-dominated front of solutions. In the last column, the numbers in bold are the selected depots for the best solution in the front. Notice that instance P04 shows the worst result in optimality, in contrast with the other two instances. Compared with P04, instances P05 and P07 have more depots or greater vehicle capacity, which is an advantage in providing a better routing solution. Moreover, P04 and P07 present a more comprehensive range of options for routing, i.e., a total of six feasible solutions, with a difference of 13% and 7%, respectively, between the minimum and maximum values for distance traveled. Instance P05 only has two solutions that match the extreme points, with a difference of 3.2% in the distance traveled, translating into a few decision-making options.

Table 2

Results for the MDVRP instances P04, P05 and P07

Instance	α	β	D_{trav}	STD_{dev}	BKS	Gap [%]	Routes of the best solution
P04 Available vehicles: 8 No. customers: 100 No. of depots: 2 Capacity: 100	0,9	0,1	1131,72	15,23	1001,59	12,99	101-56-23-67-39-25-55-101
	0,88	0,12	1140,82	14,02			101-94-96-59-95-97-101
	0,92	0,08	1143,99	10,67			102-30-20-71-65-35-9-51-102
	0,93	0,07	1176,66	10,33			101-58-40-26-12-54-4-101
	0,95	0,05	1188,68	8,36			102-18-60-84-17-45-8-48-7-88-102
	0,96	0,04	1279,55	8,00			101-98-85-57-41-22-74-2-101
P05 Available vehicles: 5 No. customers: 100 No. of depots: 2 Capacity: 200	0,91	0,09	768,39	10,23	750,03	2,45	101-92-93-91-16-86-38-42-101
	0,89	0,11	793,00	9,94			101-15-43-14-44-61-5-6-101
							102-1-50-29-24-80-68-76-102
							102-33-81-66-32-90-63-102
							102-10-11-64-49-36-46-31-102
							101-27-89-99-37-100-87-101
P07 Available vehicles: 4 No. customers: 100 No. of depots: 4 Capacity: 100	0,83	0,17	918,27	16,77	885,80	3,67	102-69-28-77-3-79-78-34-70-102
	0,89	0,11	923,26	16,10			102-52-83-82-47-19-62-102
	0,99	0,01	925,06	16,07			101-73-75-72-21-53-13-101
	0,81	0,19	937,17	15,08			102-26-53-13-6-94-95-97-87-73-21-54-102
	0,9	0,1	939,21	15,01			101-82-7-62-10-63-90-32-30-70-31-88-52-18-101
	0,95	0,05	983,34	12,76			101-89-58-40-2-57-15-43-42-37-98-93-85-61-5-101
P07 Available vehicles: 4 No. customers: 100 No. of depots: 4 Capacity: 100	0,83	0,17	918,27	16,77	885,80	3,67	101-45-46-47-36-49-64-11-19-48-8-83-101
	0,89	0,11	923,26	16,10			101-60-96-99-59-92-100-91-16-44-14-38-86-17-84-101
	0,99	0,01	925,06	16,07			102-80-68-24-29-34-78-81-33-1-69-27-28-12-102
	0,81	0,19	937,17	15,08			102-55-25-39-67-23-56-75-41-22-74-72-4-102
	0,9	0,1	939,21	15,01			102-76-50-51-20-66-65-71-35-9-79-3-77-102
	0,95	0,05	983,34	12,76			104-69-1-50-33-81-9-51-104
							104-71-35-65-66-20-30-104
							104-10-11-19-62-88-31-104
							101-18-89-6-96-99-93-5-101
							101-60-59-100-91-85-84-101
							103-87-42-14-44-38-43-15-103
							103-13-58-21-72-22-41-103
				101-82-48-47-46-8-101			
				102-3-79-78-34-29-24-102			
				103-2-57-97-37-98-92-95-94-103			
				102-54-55-25-39-4-102			
				104-52-7-36-49-64-63-90-32-70-104			
				102-76-77-68-80-102			
				103-74-75-23-67-56-73-103			
				101-83-45-17-86-16-61-101			
				102-26-40-53-27-28-12-102			

Table 3 presents the results for the MDVRP instances P03, Pr02, and Pr08. The last column shows the front of non-dominated solutions. Notice that the minimum value of distance traveled in P03 and Pr02 are closer to their respective BKS values than the instance Pr08 result, which has a GAP close to 10%. Nevertheless, the non-dominated solutions front, for instance Pr08, has greater crowding distances than those presented in P03 and Pr02, providing a broader range of possibilities for decision-making purposes.

Table 3
Results for the MDVRP instances P03, Pr02 and Pr08

Instance	α	β	D_{trav}	STD_{dev}	BKS	Gap [%]	Non-dominated solutions front
P03 Available vehicles: 3 No. customers: 75 No. of depots: 5 Capacity: 140	0,86	0,14	646,68	15,79	641,19	0,86	
	0,8	0,2	648,04	15,14			
	0,83	0,17	655,33	14,73			
	0,89	0,11	657,02	11,26			
	0,99	0,01	661,35	10,75			
	0,94	0,06	661,81	8,74			
Pr02 Available vehicles: 2 No. customers: 96 No. of depots: 4 Capacity: 195	0,96	0,04	1328,65	120,16	1307,61	1,61	
	0,99	0,01	1345,26	91,60			
	0,81	0,19	1367,78	81,67			
	0,98	0,02	1371,03	60,51			
Pr08 Available vehicles: 2 No. customers: 144 No. of depots: 6 Capacity: 190	0,96	0,04	1828,90	40,56	1666,60	9,74	
	0,86	0,14	1850,36	40,32			
	0,9	0,1	1925,37	33,94			
	0,8	0,2	1970,90	30,44			

Table 4 presents the results for the MDVRP instances P12, Pr01, and Pr07, showing a GAP of zero between the best solution found in the non-dominated front and the BKS reported in the literature. For validation purposes, the last column has presented the routes of the best solution in the non-dominated front described in columns 2 and 3 by the values in bold. The difference between the maximum and minimum distances obtained in the front, for the instances P12, Pr01, and Pr07 present a difference of 3.5%, 5.7%, and 4.4%, respectively, which means that instance Pr01 provides the broadest range in the distance traveled for the decision-making process, furthermore, Pr07 accounts with the greatest number of solutions in the front.

Table 4
Results for the MDVRP instances P12, Pr01 and Pr07

Instance	α	β	D_{trav}	STD_{dev}	BKS	Gap [%]	Routes of the best solution
P12 Available vehicles: 5 No. customers: 80 No. of depots: 2 Capacity: 60	0,99	0,01	1318,95	22,38	1318,95	0,00	81-8-16-24-32-37-29-21-13-5-81 82-45-53-61-69-77-75-40-67-59-51-43-82 81-7-15-23-31-57-65-73-38-30-22-14-6-81 82-48-56-64-72-80-79-71-63-55-47-82 81-3-11-19-27-35-34-26-18-10-2-81 81-1-9-17-25-33-36-28-20-12-4-81 82-46-54-62-70-78-76-68-60-52-44-82 82-41-49-39-74-66-58-50-42-82
	0,95	0,05	1365,82	22,38			
Pr01 Available vehicles: 1 No. customers: 48 No. of depots: 4 Capacity: 200	1	0	861,32	53,14	861,32	0,00	51-1-28-14-4-19-20-33-13-8-5-29-16-51 49-35-9-42-46-43-39-32-44-31-36-41-7-37-49 52-2-15-25-23-26-18-17-40-38-12-21-24-47-30-52 50-22-27-3-6-48-45-11-10-34-50
	0,8	0,2	893,83	45,08			
	0,91	0,09	909,08	43,42			
	0,99	0,01	911,06	23,51			
Pr07 Available vehicles: 1 No. customers: 72 No. of depots: 6 Capacity: 200	0,84	0,16	1089,56	62,84	1089,56	0,00	73-27-60-11-6-33-65-10-31-20-18-71-36-73 78-35-2-38-39-32-25-78 75-69-62-44-34-22-54-56-3-16-15-45-8-75 77-70-9-19-42-30-66-48-21-55-4-40-67-14-77 76-13-59-51-17-41-50-57-24-63-5-72-53-46-28-29-52-76 74-49-61-37-58-7-43-26-23-1-64-47-12-68-74
	0,88	0,12	1093,04	61,31			
	1	0	1100,18	60,69			
	0,95	0,05	1100,18	60,69			
	0,87	0,13	1113,78	50,22			
	0,86	0,14	1122,71	49,01			
	0,94	0,06	1137,52	48,95			
0,82	0,18	1138,57	41,28				

Moreover, the distance range could be better with more α and β values used in the runs. On the other side, the differences in standard deviation for the P12, Pr01, and Pr07 instances between the maximum and minimum distances obtained in the front, are 0%, 126% and 52.2%, respectively, which means that for the instance P12 the work load distribution is the same for the two solutions presented in the front, therefore, the routing solution with a greater distance could be discarded as the unbalance

measure is equal to that routing with a smaller distance traveled. Instance Pr01 shows the greatest difference in terms of standard deviation, being an advantage for the assessment of different alternatives contingent upon the workload distribution required in the routing, although provides less options in the front of solutions compared with the instance Pr07.

6. Concluding remarks

Logistics operation is often affected by factors related to the equilibrium between the routes for goods transportation purposes. This situation is translated into a sense of fairness since the routes can be performed by different drivers and vehicle features, regardless of the vehicle's capacity. This work proposed a hybrid methodology encompassing the Chu-Beasley Genetic Algorithm with the Variable Neighborhood Search Algorithm, to address this perspective in the VRP with multiple depots and predetermined location customers. The hybridization of metaheuristic techniques promotes a rapid convergence in the algorithm, given that the local exploration allows finding promising quality regions that cannot be found with the traditional genetic operators. Two terms are in conflict in the objective function: the total distance traveled by vehicles and the standard deviation of the routes. This latter represents a significant index for route balancing, considering that the greater the standard deviation of the routes, the shorter the total distance traveled.

Conversely, small values of standard deviation are found for routing solutions with longer distances in the routes, which means that the routing solutions are more balanced. It can be observed that the number of solutions presented in the non-dominated front depends on the resolution for the values of α and β that correspond to the weights provided for each term of the objective function. The methodology solved some large-size instances of the literature, reaching the optimal solution for three MDVRP benchmark instances. Other experimenters reached near-optimal solutions with GAP close to zero. The non-dominated front of solutions reflects a range of possibilities that support decision-making and managerial insight. In future works, it is proposed to improve the methodology by using population initialization procedures, particularly for the MDVRP, and adapt the embedded algorithm to other routing problems, such as the VRP with time windows.

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References

- Borgulya, I. (2008). An algorithm for the capacitated vehicle routing problem with route balancing. *Central European Journal of Operations Research*, 16, 331-343.
- Chao, I. M., Golden, B. L., & Wasil, E. (1993). A new heuristic for the multi-depot vehicle routing problem that improves upon best-known solutions. *American Journal of Mathematical and Management Sciences*, 13(3-4), 371-406.
- Chu, P. C., & Beasley, J. E. (1997). A genetic algorithm for the generalised assignment problem. *Computers & Operations Research*, 24(1), 17-23.
- de Oliveira, F. B., Enayatifar, R., Sadaei, H. J., Guimarães, F. G., & Potvin, J. Y. (2016). A cooperative coevolutionary algorithm for the multi-depot vehicle routing problem. *Expert Systems with Applications*, 43, 117-130.
- Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE transactions on evolutionary computation*, 6(2), 182-197.
- Escobar, J. W., Linfati, R., Toth, P., & Baldoquin, M. G. (2014). A hybrid granular tabu search algorithm for the multi-depot vehicle routing problem. *Journal of heuristics*, 20, 483-509.
- Filipec, M., Škrlec, D., & Krajcar, S. (2000). Genetic algorithm approach for multiple depot capacitated vehicle routing problem solving with heuristic improvements. *International Journal of Modelling and Simulation*, 20(4), 320-328.
- Galindres-Guancha, L., Toro-Ocampo, E., & Rendón, R. (2018). Multi-objective MDVRP solution considering route balance and cost using the ILS metaheuristic. *International Journal of Industrial Engineering Computations*, 9(1), 33-46.
- Garcia-Najera, A., & Bullinaria, J. A. (2011). An improved multi-objective evolutionary algorithm for the vehicle routing problem with time windows. *Computers & Operations Research*, 38(1), 287-300.
- Geetha, S., Vanathi, P. T., & Poonthalir, G. (2012). Metaheuristic approach for the multi-depot vehicle routing problem. *Applied Artificial Intelligence*, 26(9), 878-901.
- Ho, W., Ho, G. T., Ji, P., & Lau, H. C. (2008). A hybrid genetic algorithm for the multi-depot vehicle routing problem. *Engineering applications of artificial intelligence*, 21(4), 548-557.
- Hou, D., Fan, H., & Ren, X. (2021). Multi-Depot Joint Distribution Vehicle Routing Problem Considering Energy Consumption with Time-Dependent Networks. *Symmetry*, 13(11), 2082.
- Hou, D., Fan, H., Ren, X., Tian, P., & Lv, Y. (2021). Time-dependent multi-depot heterogeneous vehicle routing problem considering temporal-spatial distance. *Sustainability*, 13(9), 4674.
- Jayarathna, D. G. N. D., Lanel, G. H. J., & Juman, Z. A. M. S. (2021). Survey on ten years of multi-depot vehicle routing problems: mathematical models, solution methods and real-life applications. *Sustainable Development Research*, 3(1), p36-p36.

- Jayarathna, N., Lanel, J., & Juman, Z. (2020). View of Five years of multi-depot vehicle routing problems. *Journal of Sustainable Development Transport and Logistics*, 109-123.
- Jozefowicz, N., Semet, F., & Talbi, E. G. (2007). Target aiming Pareto search and its application to the vehicle routing problem with route balancing. *Journal of Heuristics*, 13, 455-469.
- Jozefowicz, N., Semet, F., & Talbi, E. G. (2009). An evolutionary algorithm for the vehicle routing problem with route balancing. *European Journal of Operational Research*, 195(3), 761-769.
- Karakatić, S., & Podgorelec, V. (2015). A survey of genetic algorithms for solving multi depot vehicle routing problem. *Applied Soft Computing*, 27, 519-532.
- Li, Y., Qian, B., Hu, R., Wu, L. P., & Liu, B. (2019). Two-stage algorithm for solving multi-depot green vehicle routing problem with time window. In *Intelligent Computing Theories and Application: 15th International Conference, ICIC 2019, Nanchang, China, August 3–6, 2019, Proceedings, Part I 15* (pp. 665-675). Springer International Publishing.
- Li, Y., Soleimani, H., & Zohal, M. (2019b). An improved ant colony optimization algorithm for the multi-depot green vehicle routing problem with multiple objectives. *Journal of cleaner production*, 227, 1161-1172.
- Liu, R., Jiang, Z., & Geng, N. (2014). A hybrid genetic algorithm for the multi-depot open vehicle routing problem. *OR spectrum*, 36, 401-421.
- Luo, J., & Chen, M. R. (2014). Improved shuffled frog leaping algorithm and its multi-phase model for multi-depot vehicle routing problem. *Expert Systems with Applications*, 41(5), 2535-2545.
- Luo, J., Li, X., & Chen, M. R. (2012). A Novel Meta-heuristic for the Multi-depot Vehicle Routing Problem. In *Information Computing and Applications: Third International Conference, ICICA 2012, Chengde, China, September 14-16, 2012. Proceedings, Part I 3* (pp. 216-224). Springer Berlin Heidelberg.
- Mancini, S., Gansterer, M., & Hartl, R. F. (2021). The collaborative consistent vehicle routing problem with workload balance. *European journal of operational research*, 293(3), 955-965.
- Matl, P., Hartl, R. F., & Vidal, T. (2018). Workload equity in vehicle routing problems: A survey and analysis. *Transportation Science*, 52(2), 239-260.
- Mirabi, M. (2014). A hybrid electromagnetism algorithm for multi-depot periodic vehicle routing problem. *The International Journal of Advanced Manufacturing Technology*, 71(1-4), 509-518.
- Montoya, O. D., Gil-González, W., & Orozco-Henao, C. (2020). Vortex search and Chu-Beasley genetic algorithms for optimal location and sizing of distributed generators in distribution networks: A novel hybrid approach. *Engineering Science and Technology, an International Journal*, 23(6), 1351-1363.
- Moonsri, K., Sethanan, K., Worasan, K., & Nitisiri, K. (2021). A hybrid and self-adaptive differential evolution algorithm for the multi-depot vehicle routing problem in egg distribution. *Applied Sciences*, 12(1), 35.
- Networking and Emerging Optimization. (2006). The VRP web. Retrieved from https://www.bernabe.dorronsoro.es/vrp/index.html?Problem_Instances/CVRPTWInstances.html
- Ombuki-Berman, B., & Hanshar, F. T. (2009). Using genetic algorithms for multi-depot vehicle routing. In *Bio-inspired algorithms for the vehicle routing problem* (pp. 77-99). Berlin, Heidelberg: Springer Berlin Heidelberg.
- Peng, B., Wu, L., Yi, Y., & Chen, X. (2020). Solving the multi-depot green vehicle routing problem by a hybrid evolutionary algorithm. *Sustainability*, 12(5), 2127.
- Prabu, U., Ravisasthiri, P., Sriram, R., Malarvizhi, N., & Amudhavel, J. (2019). EODVGA: an enhanced ODV based genetic algorithm for multi-depot vehicle routing problem. *EAI Endorsed Transactions on Scalable Information Systems*, 6(21), e8-e8.
- Renaud, J., Laporte, G., & Boctor, F. F. (1996). A tabu search heuristic for the multi-depot vehicle routing problem. *Computers & Operations Research*, 23(3), 229-235.
- Shen, L., Tao, F., & Wang, S. (2018). Multi-depot open vehicle routing problem with time windows based on carbon trading. *International journal of environmental research and public health*, 15(9), 2025.
- Singh, V., Ganapathy, L., & Pundir, A. K. (2021). An improved genetic algorithm for solving multi depot Vehicle Routing Problems. In *Research anthology on multi-industry uses of genetic programming and algorithms* (pp. 375-402). IGI Global.
- Skok, M., Skrlec, D., & Krajcar, S. (2000, August). The genetic algorithm method for multiple depot capacitated vehicle routing problem solving. In *KES'2000. Fourth International Conference on Knowledge-Based Intelligent Engineering Systems and Allied Technologies. Proceedings (Cat. No. 00TH8516)* (Vol. 2, pp. 520-526). IEEE.
- Subramanian, A., Uchoa, E., & Ochi, L. S. (2013). A hybrid algorithm for a class of vehicle routing problems. *Computers & Operations Research*, 40(10), 2519-2531.
- Surekha, P., & Sumathi, S. (2011). Solution to multi-depot vehicle routing problem using genetic algorithms. *World Applied Programming*, 1(3), 118-131.
- Tang, Y. L., Cai, Y. G., & Yang, Q. J. (2015). Optimization of Multi-Depot Heterogeneous Incident Vehicle Routing Problem with Soft Time Windows based on an Improved Ant Colony Optimization. *Advanced Materials Research*, 1061, 1108-1117.
- Wink, S., Bäck, T., & Emmerich, M. (2012, June). A meta-genetic algorithm for solving the capacitated vehicle routing problem. In *2012 IEEE congress on evolutionary computation* (pp. 1-8). IEEE.
- Yu, V. F., Aloina, G., Susanto, H., Effendi, M. K., & Lin, S. W. (2022). Regional Location Routing Problem for Waste Collection Using Hybrid Genetic Algorithm-Simulated Annealing. *Mathematics*, 10(12), 2131.

- Yücenur, G. N., & Demirel, N. Ç. (2011). A new geometric shape-based genetic clustering algorithm for the multi-depot vehicle routing problem. *Expert Systems with Applications*, 38(9), 11859-11865.
- Zacharia, P., Drosos, C., Piromalis, D., & Papoutsidakis, M. (2021). The vehicle routing problem with fuzzy payloads considering fuel consumption. *Applied Artificial Intelligence*, 35(15), 1755-1776.
- Zhang, W., Gajpal, Y., Appadoo, S. S., & Wei, Q. (2020). Multi-depot green vehicle routing problem to minimize carbon emissions. *Sustainability*, 12(8), 3500.
- Zhou, W., Song, T., He, F., & Liu, X. (2013). Multiobjective vehicle routing problem with route balance based on genetic algorithm. *discrete Dynamics in Nature and Society*, 2013.
- Zhou, Z., Ha, M., Hu, H., & Ma, H. (2021). Half open multi-depot heterogeneous vehicle routing problem for hazardous materials transportation. *Sustainability*, 13(3), 1262.



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