

Generation of distribution routes with shorter distances and fewer vehicles using the simulated annealing algorithm

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ABSTRACT

The vehicle routing problem (VRP) is still a persistent challenge in society, and can be considered a combinatorial optimization problem, where a fleet of delivery vehicles must satisfy the demand of customers sharing the same depot, minimizing the transport distance. The objective of this research is to propose a method to generate distribution routes that minimize both the number of vehicles used and the total distance traveled. To this end, an initial solution is used, on which the Greedy algorithm is applied, followed by the simulated annealing (SA) algorithm, manipulating the exchange techniques, insertion methods, parameter adjustments within the algorithm and applying the penalty as a mechanism to avoid the excessive use of trucks or the assignment of routes that exceed the allowed capacity. The proposal was validated using four datasets, as a result, the general averages of the reduction in distance, changes and penalty cost are shown: The Greedy algorithm reduced the distance by 5.71%, in trucks to 16.57%, in penalty cost to 14.71%; then, applying the SA algorithm, a better efficiency was achieved by reducing the distance by 10.36%, 20.08% in trucks and 18.64% in penalty cost. In this way, the use of vehicles in the distribution routes is optimized, which could contribute to the reduction of vehicular traffic and the reduction of CO2 emissions, thus favoring the environment.

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1. INTRODUCTION

In an increasingly interconnected world, where supply chains and e-commerce are constantly growing, route optimization has become a priority for companies and governments. According to the report [1], in the US, e-commerce has intensified, generating a demand for last-mile deliveries that grew by 30% annually during the pandemic, which has caused companies such as Amazon and unified particle swarm (UPS) to invest in advanced route optimization algorithms to reduce costs and improve product delivery efficiency. In Latin America, vehicle routing problem (VRP) is also affected by informality in the logistics sector. In Mexico, for example, it is estimated that 40% of transportation companies operate informally [2], which prevents the implementation of advanced technological solutions. In addition, the lack of accurate data on traffic conditions and optimal routes limits the efficiency of routing systems.

Vehicle routing is a fundamental challenge in logistics optimization and planning and is present in a wide range of industry applications, from vehicle fleet management to product distribution, public transportation and waste collection, among others, all subject to specific constraints. These constraints include vehicle carrying capacity, time windows in which locations can be visited, and distance limitations.

Operations related to supply chain and logistics are often costly. Product distribution is one of the most important stages of the supply chain, as it involves the delivery of products to retailers and/or customers. However, this process can consume large amounts of time, economic resources and environmental pollution. Therefore, this problem is modeled in many situations as a VRP [3].

According to [4], the load distribution of a fleet of trucks delivering loads from a depot to multiple destinations can be complicated when there are many routes and destinations involved. One of the biggest challenges in vehicle routing is the complexity of the problem because as the number of vehicles, deliveries and constraints increases, the number of possible routes also increases exponentially, despite these challenges, effectively solving VRPs can have a significant impact on logistics efficiency and cost reduction for companies that rely on the delivery and collection of goods and services. One of the problems addressed by operations research is the VRP, which is a key function in logistics systems and involves the flow of products from manufacturing plants or distribution centers through a transportation network to consumers. There have been several studies on VRP since decades ago, first proposed in research in its classical formulation [5] and since then it has been a widely studied problem.

The origin of the VRP comes from years ago and is introduced by Dantzing and Ramser, who represented a real application related to the delivery of gasoline to service stations and proposed the mathematical formulation to this problem, which arises as a generalization of the classical traveling salesman problem (TSP) in which a salesman has to travel to a series of customers only once, and then return to the starting point. The VRP is considered as a problem that starts in a central depot or warehouse, which has a fleet of vehicles that must serve a set of customers scattered in a geographical area [6].

There are different algorithms that allow to traverse the generated solutions to find optimal solutions or get close to them, such as the genetic algorithm (GA), ant colony algorithm and hybrid search algorithm. However, the VRP is a typical non-deterministic polynomial problem, the exact solution is only possible when the number of demand points and road sections is small, so it is generally difficult to obtain a global optimal or satisfactory solution [7]. An alternative is the simulated annealing (SA) algorithm. This is a stochastic optimization technique, i.e., the search for the optimal solution uses random elements. This optimization method has its origin in statistical mechanics and is based on mimicking the annealing process used in metallurgy.

According to [8], the time-dependent VRP (TDVRP) with flexible time windows and stochastic factors, such as variability in vehicle speeds and travel times, is addressed. To solve this problem, the authors propose a hybrid algorithm (HA) that combines the scanning algorithm to generate initial solutions with an improved particle swarm optimization (PSO) algorithm to optimize these solutions. This hybrid approach seeks to minimize the total distribution cost, considering customer time constraints and uncertainty in traffic conditions.

In the study by [9], the multi-depot petrol station refueling problem with time windows (MPSRPTW) is addressed, they set out to optimize the delivery of petroleum products. Each depot has a heterogeneous fleet of compartmentalized trucks, and key decisions include routing, truck allocation, schedule planning, and product distribution across compartments. The proposed mathematical model selects feasible routes to maximize daily revenue, using heuristics to handle the extensive set of possible routes.

According to [10], to meet the diverse and specific demands of customers, a vehicle scheduling by pickup and delivery model has been implemented. To address this problem, a HA was designed, which combines a GA with variable neighborhood search, stages that incorporates the concept of temporal-spatial distance. The results of the study show that the initial solution that considers the temporal-spatial distance offers clear advantages in terms of algorithm efficiency and solution quality.

The objective of this research is to design an optimization model based on the SA algorithm, specifically adapted for the capacity capacitated vehicle routing problem (CVRP). This model minimizes at the same time the number of vehicles required, and the total distance traveled in the distribution of products. To achieve this objective, an integrated objective function is designed that includes, in addition to calculating the distances, a penalty for the excessive use of vehicles, which promotes the adequate and efficient use of the available fleet.

2. RELATED WORK

In research [11], a solution to the two-dimensional CVRP (2L-CVRP) is proposed by developing a heuristic based on open spaces to identify the route packing patterns and an efficient data structure (Trie) to

record the feasibility information and control the effort invested in each route. In class 1 instances, it is observed that implementation by SA was less expensive than other methods. In class 2-5 instances, it ties in 7 instances with the best solutions and finds better solutions for 23 other instances, especially in the large ones.

In research [12], they propose a SA algorithm for the VRP with time windows and synchronization constraints (VRPTWSyn). In this problem, each customer is associated with a time window that represents the time interval during which the customer is available to receive a delivery. If the vehicle arrives too early, it must wait until the opening of the time window, but late arrivals are not allowed. The visits associated with a particular customer must be synchronized by starting at the same time. The solution proposed in [5], introduces several heuristic methods to solve the vehicle routing and scheduling problem with time windows (VRSPTW).

In [13], an innovative algorithm fusing SA and variable neighborhood descent (VND) techniques was proposed to solve the challenging Heterogeneous Fleet VRP with multiple forward/reverse cross-docks (HF-VRPMFRCD), which addresses both forward and reverse logistics. This approach considered a wide range of vehicles with different load capacities and transportation costs, in addition to multiple cross-docking operations spanning both the direct and reverse process. The results obtained by this algorithm demonstrate its ability to provide optimal solutions in small-scale cases and superior solutions compared to the GUROBI solver in more complex HF-VRPMFRCD instances.

In [14] they addressed the VRP with simultaneous pickup and delivery and time windows (VRPSPDTW), a complex variant of the VRP that belongs to the class of NP-hard problems, for which they develop a SA algorithm that combines local search strategies with a cooling program that controls the probability of accepting suboptimal solutions to escape local minima and find high-quality global solutions.

The solution proposals of [15] and [16] are very similar, moreover, both investigations contrast their results with solution methods based on GAs. Obtaining average and maximum percentage differences of -0,22 % and 1,61 % respectively. The results in [15] similarly find optimal solutions for all the cases evaluated.

In research [17], they propose a metaheuristic to solve the CVRP based on the SA algorithm. In this research, the customer's demand with respect to its supplier is known. However, for product delivery, the capacity of each vehicle must be constrained. The researchers maintained their goal of decreasing the weight on each path as long as it is possible to deliver all products to the customer.

Several solutions exist in the field of vehicle routing to address different variants of the problem. On one hand, in the paper [18], a solution for the periodic CVRP (PCVRP) is proposed using the SA algorithm implemented in the Julia programming language. This approach optimizes the routes of a furniture parts manufacturing company in Turkey, achieving a significant reduction in the distance traveled and the number of vehicles used, improving efficiency by 88.72% with respect to previous solutions, although with a longer computational time. On the other hand, the paper [19] addresses the open VRP (OVRP), in which vehicles do not return to the depot. The Clarke-Wright (CW) heuristic algorithm is modified, incorporating procedures such as open route construction and post-route improvements through insertion operators and swaps.

In research [20], they present an approach based on a dual GA combined with SA to solve the VRP with multiple depots and traffic networks with time-varying speeds, taking into account the minimization of distribution costs and carbon emissions. In the study conducted by [21], vehicle trajectory optimization using IoT technology and GA was investigated. First, the optimization of the traditional GA was performed by analyzing the encoding, fitness function, selection, crossover and mutation operators. A crossover probability of 0.6 and a mutation probability of 0.1 were established.

In the study described in reference [22], a solution to reduce distribution costs for a dairy cooperative in India by applying clustering and capacitated routing techniques is proposed. Using the k-means algorithm to divide delivery locations into clusters of similar size based on proximity, and respecting maximum vehicle capacities, the clusters were assigned to local stockists.

In [23], the paper presents an optimization algorithm for the transportation and distribution of vegetables that minimizes the cost, transportation time and number of vehicles used, considering constraints such as vehicle capacity and specific time windows to maintain the freshness of the products. A hybrid approach is proposed based on a GA enhanced with a SA process, using the adaptive Metropolis acceptance criterion. Besides, in [24], they proposed a novel approach using annealing neural networks based on Lagrange barrier functions. These methods focused on addressing both linear equality constraints using the Lagrange function and reaching near-global or global optimal solutions using the barrier function.

Study [25] analyzes the optimization of fishing vessel routes in twenty-six fishing landing bases to the national fishing port using the CVRP model, which considers constraints such as distance, number of vessels, capacity, catches, travel time and operational costs. Guided local search (GLS) and SA methods with Google OR-Tools were used, proving to be efficient in heuristic problems. The results showed that, for two and three ships, both methods generated similar results (290 and 355 miles), but with four ships, SA was more efficient (439 miles versus 464 for GLS).

3. GENERATION OF DISTRIBUTION ROUTES WITH FEWER VEHICLES USING THE SIMULATED ANNEALING ALGORITHM

This study focuses on the solution of the CVRPs, which is a variant of VRP, through a metaheuristic approach (SA). For this purpose, we propose a methodology consisting of five stages: data collection and organization, generation of an initial solution using the Greedy algorithm, model definition, search for the optimal solution through SA using neighborhood operators (swapping, insertion and inversion) to explore the solution space, and analysis of the results.

The objective function integrates two main components: travel distance and a penalty for excessive truck use, promoting alternatives that minimize both factors simultaneously. The SA algorithm dynamically adjusts the temperature and search intensity, promoting a balanced transition between exploration and exploitation, thus preventing premature convergence.

A. Data collection and organization

Standardized examples from the CVRP Library (CVRPLIB), a widely used vehicle routing database available at <http://vrp.galagos.inf.puc-rio.br/index.php/en/> were used. The instances chosen include the coordinates of each customer, the corresponding demands and the maximum vehicle capacity. The data were used in .vrp format obtained from both online resources and local files that had been previously downloaded.

Table 1 shows the initial data within the dataset the data set collected from CVRPLIB, the first column is the name of the data set A, B, C, E, X, the second column is “k” the solution with 5 vehicles, the third column is “N° vertices” is the number of points or numbers of customers to distribute, the fourth column is “Q” is the carrying capacity of the vehicle, the last column “Distance” is the cost distance traveled by the vehicles in the distribution.

Table 1. CVRPLIB data set collected

Dataset	k	N° of vertices	Q	Distance
A-n32-k5	5	32	100	784
B-n31-k5	5	31	100	672
E-n101-k14	14	101	112	1,071
X-n101-k25	25	101	206	27,591

B. Generation of the initial solution

The initial solution is generated using the Greedy algorithm, which creates sequential routes choosing at each stage the customer closest to the last visited node, as long as the remaining vehicle capacity allows it. This process is repeated until all client nodes have been assigned to some route, locally optimizing the distance and complying with capacity constraints:

- It starts at depot (Vertex 0)
- The node closest to the visited node is selected to be added to the route.
- Check if the sum of customer demands on the route exceeds the vehicle capacity(Q), start a new route from the depot.
- Repeat this process until the load limit per truck is reached.
- Terminate when all customers have been visited and routes have been assigned.

With the result of the initial solution of the Greedy algorithm the SA model is defined this to optimize and improve the quality of the solutions.

C. Definition of the SA model

The problem is mathematically modeled by means of complete directed graphs $G=(V, A)$, where each vertex represents customers with associated demand and edges whose weight is calculated by the Euclidean distance between two vertices.

There is a single depot, represented by vertex 0, from where vehicles depart and return after completing their routes. Each vertex has a position in a two-dimensional plane, defined by its X and Y coordinates.

Figure 1 shows the graphical representation of the VRP model, the nodes labeled “Node with demand” represent the customers (A, B, C, D, E, F, G), while the depot (black square) is in the center, identified with the number 0.

Where,

- Vehicle 1: Serves nodes A, B, C and return to its position,
- Vehicle 2: Serves nodes D, E.
- Vehicle 3: Serves nodes F, G.

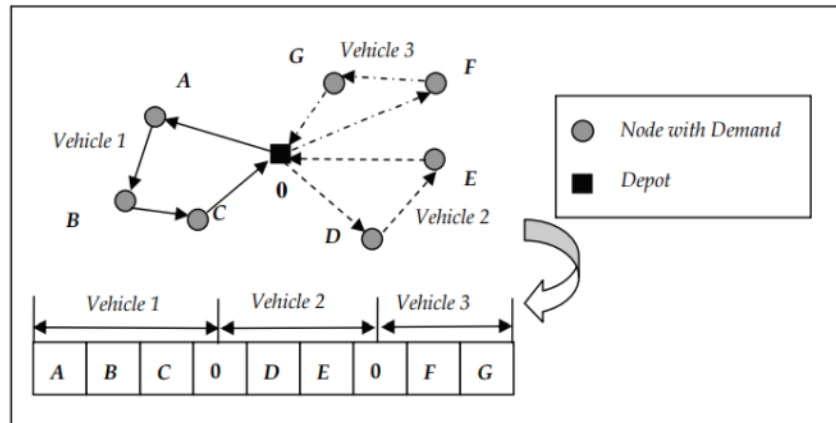


Figure 1. Graphical representation of the VRP model

Each vertex is located in a two-dimensional Euclidean space, and the edge weights represent the Euclidean distance between pairs of nodes. The objective function to be minimized consists of two elements: the total distance traveled on all vehicle routes and a penalty criterion proportional to the number of vehicles employed. This dual-objective formulation promotes solutions that maximize both logistical efficiency (shortest distance traveled) and fleet utilization (fewest number of vehicles), effectively penalizing solutions that involve excessive vehicle usage.

D. Optimal Solution Search

The SA is a metaheuristic optimization algorithm that allows to explore the solution space to find the optimal solution, it is also able to accept worsening moves according to a certain probability defined by the control variables, where the probability of accepting worsening moves will depend on how bad the new solution is compared to the current solution. The greater the difference, the more difficult it will be to accept such a move. The probability of acceptance will depend mainly on a control variable T (temperature), which decreases in each iteration, when T is high and more worsening moves are accepted the solution indicates that more exploration of the search space is allowed to be performed. On the other hand, as T decreases, the amount of acceptance of moves that worsen the solution also decreases, then the solution is concentrated in a certain location.

This research implements the SA algorithm adapted and applied to the problem of route generation for vehicles with limited capacity, which explores the set of solutions through modifications based on proximity operators: node exchange, relocation and sequence reversal.

- Exchange (2 elements): “One-to-one exchange”. This transformation made it possible to exchange the position of two clients within the solution. The two clients are chosen randomly and can belong to the same route or to different routes. If one of the selected clients is a depot, a special procedure is performed to ensure that the solution remains valid.
- Relocate (1 element): “Delete and Insert”. In this technique, a customer is randomly selected from the sequence and inserted into another position. The relocation can occur within the same route or between different routes, depending on the structure of the solution. If the reassigned customer is a depot, two routes are combined and at the same time, another route is split in two to preserve the consistency of the solution.
- Invert sequence: “Partial reversal”. In this transformation, given two reference points (i, j) , the substring between them is extracted and reinserted in the same position, but in an inverted manner (j, i) . As in other transformations, this technique can be applied both within a path and between different paths. As a result, a solution different from the original one is generated.

Each neighboring solution is evaluated on the basis of its total cost (distance covered). If the new solution has a lower cost, it is considered as the new current solution. Otherwise, it can be accepted with a certain probability depending on the difference in cost and current temperature, which allows it to leave the optimal location. This iterative process is performed with a certain number of cycles or until the temperature reaches the threshold.

We propose the flowchart using the SA algorithm applied to the problem of generating routes for vehicles with limited capacity in Figure 2.

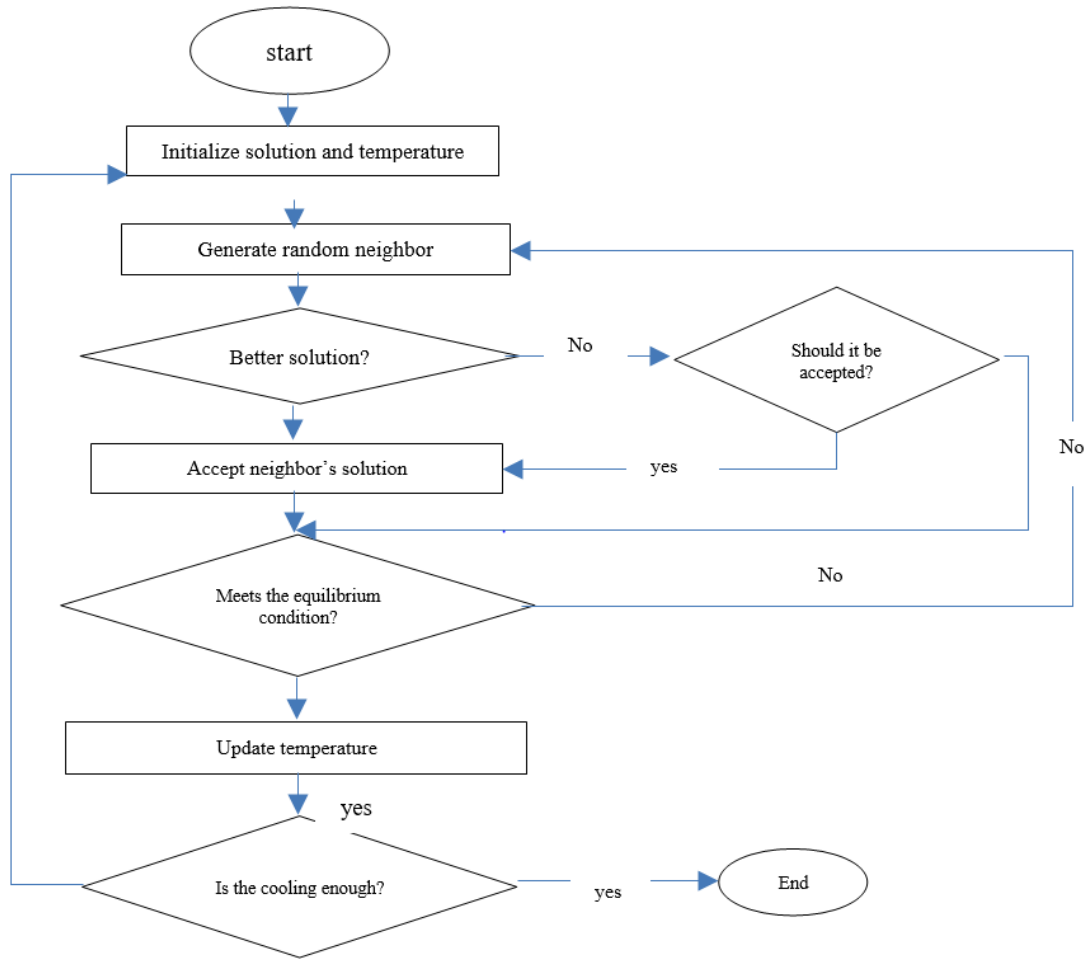


Figure 2. Flowchart of the SA algorithm applied to the capacitated VRP

E. Analysis and validation of results

For the validation of results, metrics have been used to guarantee the robustness and quality of the solutions obtained. The metrics used are,

- Total distance traveled: evaluates the efficiency of the routes in total kilometers.

$$D = \sum_{k=1}^K \sum_{i=0}^{n_k-1} d(v_i^{(k)}, v_{i+1}^{(k)})$$

Where,

- K is the number of vehicles used
- n_k is the number of nodes on vehicle k's route
- $d(v_i, v_j)$ represents the Euclidean distance between nodes i, j
- Each route starts and ends at the same depot
- Number of trucks used: measures fleet reduction capacity.

$$k = \text{total number of routes generated}$$

- Penalized cost: Integrates the total distance and penalty for excessive use of vehicles, providing a more realistic view of the economic impact.

$$C = D + \alpha \cdot K$$

Where,

- D is the distance traveled
- k is the number of vehicles used
- α is a penalty factor
- Convergence iterations: Determines the stability of the solution and in how many iterations the process stabilizes.
- Computational time: Verifies the computational efficiency to guarantee feasible solutions in reasonable time.
- Route variance: Evaluates the equilibrium in the allocation of customers per truck.

$$\sigma^2 = \frac{1}{K} \sum_{k=1}^K (qk - \bar{q})^2 \text{ con } \bar{q} = \frac{1}{K} \sum_{k=1}^K qk$$

Where,

- qk is the total load assigned to vehicle k
- $\bar{q}$ is the average load per vehicle
- Percentage comparison with respect to the known optimum: To measure how close the final solution is to the optimal solution reported in standard databases.

$$\text{Percentage difference} = \left(\frac{C_{\text{model}} - C_{\text{optimal}}}{C_{\text{optimal}}} \right) \cdot 100$$

Donde,

- C_{model} is the penalized cost obtained
- C_{optimal} is the optimal value recorded in the literature

On the other hand, the graphical representation in three stages (initial solution, Greedy solution and solution after SA) helps to have a comparative visual analysis. The iterations in which significant improvements occur are also recorded and a sensitivity analysis is performed against changes in initial temperature, cooling rate and neighborhood size. This extended validation ensures that optimal or very close to optimal solutions are obtained, which are robust and consistent.

The proposed model provides a robust approach that allows decision makers to lower operational costs and evaluate the impact of each variation in the number of vehicles and route effectiveness.

4. RESULTS AND DISCUSSION

To perform the test and validation of the proposal we have used 4 datasets of the CVRPLIB which is visible at <http://vrp.galagos.inf.puc-rio.br/index.php/en/>.

In the experiment we have used 4 datasets A, B, E, X see Table 1. The results obtained from the implementation of the proposed algorithm are shown below, it is distinguished in three stages: initial solution, refined Greedy and enhanced SA. Each of these levels facilitates the observation of the gradual improvement in terms of total distance traveled, number of trucks used, penalized cost, execution time and number of iterations until convergence is reached.

Table 2 compares three methods applied to the A-n32-k5 dataset, which includes 32 customers. The initial solution, generated with the Greedy algorithm, requires 5 trucks, travels a total of 790 km and generates a penalized cost of 3290. By applying a refined version of the Greedy algorithm, and after 50 iterations of adjustment, significant improvements were obtained: The total distance was reduced by 3.16% (from 790 km to 765 km), the number of trucks decreased from 5 to 4, representing an improvement of 20%, and the penalized cost was reduced by 15.96% (from 3290 to 2765).

Table 2. Results of tests performed with A-n32-k5 datasets

Dataset	Clients (nodes)	Method	Total distance (km)	Trucks	Penalized Cost	Iterations	Improvement over distance (%)	Improvement over trucks (%)	Improvement over cost (%)	Run time (s)
A-n32-k5	32	Initial Solution	790	5	3,290	Generated with Greedy	-	-	-	1.5
		Refined Greedy	765	4	2,765	50 iterations of adjustment	3.16	20	15.96	2.0
		Enhanced SA	715	3	2,215	Convergence on 95	6.54	25	19.89	18.0

Finally, by applying the SA algorithm, an even more efficient solution was achieved after 95 iterations: The total distance was reduced to 715 km, representing a 6.54% improvement over the initial solution, only 3 trucks were used, achieving a 25% improvement, and the penalized cost decreased to 2215, with an improvement of 19.89%. Table 3 presents the results of the vehicle routing optimization using the B-n31-k5 dataset, involving 31 customers. In the initial solution, generated with the Greedy algorithm, 5 trucks were taken to cover a total distance of 845 km, with a penalized cost of 3345.

When applying the Greedy algorithm (after 55 iterations), significant improvements were observed: The total distance was reduced by 6.51% (from 845 km to 790 km), with respect to fleets it was reduced by 4 trucks (20% less), and the penalized cost decreased to 2890, representing an improvement of 13.60%.

Subsequently, with the implementation of the Enhanced SA algorithm, after 100 iterations until convergence was reached, more efficient results were obtained: The total distance decreased to 755 km, with a further improvement of 4.43% over the previous solution, the number of trucks was optimized to 3, implying an improvement of 25% compared to the initial solution, and the penalized cost was reduced to 2255, achieving an improvement of 21.97% over the Greedy method.

Table 4 shows the results obtained by applying different optimization methods on the E-n101-k14 dataset, which considers 101 customers. The initial solution was generated with 14 trucks, traveling a total of 3100 km and generating a penalized cost of 10100. Improvement with Greedy after 70 iterations, a significant improvement was obtained: The distance was reduced by 7.10%, down to 2880 km. The number of trucks was optimized to 12, representing an improvement of 14.29%. And the penalized cost was reduced to 8680, an improvement of 14.06% over the initial solution.

Table 3. Results of tests performed with B-n31-k5 datasets

Dataset	Clients (nodes)	Method	Total distance (km)	Trucks	Penalized Cost	Iterations	Improvement over distance (%)	Improvement over trucks (%)	Improvement over cost (%)	Run time (s)
B-n31-k5	31	Initial Solution	845	5	3,345	Generated with Greedy	-	-	-	1.6
		Refined Greedy	790	4	2,890	55 iterations of adjustment	6.51	20	13.60	2.3
		Enhanced SA	755	3	2,255	Convergence on 100	4.43	25	21.97	20.0

Table 4. Results of tests performed with E-n101-k14 datasets

Dataset	Clients (nodes)	Method	Total distance (km)	Trucks	Penalized Cost	Iterations	Improvement over distance (%)	Improvement over trucks (%)	Improvement over cost (%)	Run time (s)
E-n101-k14	101	Initial Solution	3,100	14	10,100	Generated with Greedy	-	-	-	3.0
		Refined Greedy	2,880	12	8,680	70 iterations of adjustment	7.10	14.29	14.06	5.9
		Enhanced SA	2,760	10	7,760	Convergence on 120	4.17	16.67	10.60	52.0

Optimizing with the SA algorithm in 120 iterations until reaching convergence, an efficient solution was achieved, the total distance decreased to 2760 km, representing an improvement of 4.17% over the previous solution, the number of changes decreased to 10, which implies an improvement of 16.67%. The penalized cost decreased to 7760, which is an improvement of 10.60% compared to the previous solution.

Finally, Table 5 shows the results obtained by applying three optimization methods on the dataset X-n101-k25, involving 101 customers. In the initial solution, 25 trucks were used, traveling 28,150 km and generating a penalized cost of 153,650. Applying the Greedy algorithm, after 80 iterations, improvements were observed, the distance was reduced to 26,720 km, which represents an improvement of 5.08%, the number of trucks decreased to 22, with an improvement of 12%, and the penalized cost decreased to 132,720, improving by 13.62% with respect to the initial solution. Optimizing with the SA algorithm achieved improvements, with 135 iterations until convergence, a more efficient solution was achieved: The total distance was reduced to 25,800 km, with an additional improvement of 3.44%, only 19 trucks were needed, implying an improvement of 13.64%, and the penalized cost was reduced to 127,300, representing an improvement of 4.08% over the previous solution.

From the analysis of the four datasets, it is shown that each of the applied methods presents progressive improvements. Calculating the averages: The solution with the Greedy algorithm managed to reduce the total distance by 5.71%, the reduction in number of trucks by 16.57% and reduced the penalized

cost by 14.71% with respect to the initial solution. Looking for more efficiency, the SA algorithm offered even more efficient results on average: the distance was reduced by 10.36%, the use of trucks decreased by 20.08%, and the penalized cost decreased by 18.64%, compared to the initial solution. These results show that the algorithm provides an optimal solution.

Figure 3 shows the evidence, with numerical accuracy, of the decreasing trend of three key variables: total distance traveled, number of trucks used and penalized cost, throughout the stages of initial solution, refined Greedy and optimization by means of SA. From a technical perspective, it can be seen that the improvement curve is more accentuated in the passage from the initial solution to Greedy, consolidating with SA, where the reductions are stabilized and optimized. The graphical analysis confirms the model's ability to minimize logistic resources without compromising the trajectory, reducing fleet overuse and excessive distances. This graphical representation, supported by numerical analysis, confirms the algorithm's ability to balance operational efficiency and resource usage, leading to reduced fleet overuse and excessive distance, which is particularly notable in large-scale datasets such as X-n101-k25, where scalability and methodological resilience allow for sustained convergence towards highly efficient solutions.

It is also important to recognize that the SA algorithm is nondeterministic, so it is probably not possible to recreate exactly the same results, even with the same starting parameters, hardware, and software specifications.

Table 5. Results of tests performed with X-n101-k25 datasets

Dataset	Clients (nodes)	Method	Total distance (km)	Trucks	Penalized Cost	Iterations	Improvement over distance (%)	Improvement over trucks (%)	Improvement over cost (%)	Run time (s)
X-n101-k25	101	Initial Solution	28,150	25	153,650	Generated with Greedy	-	-	-	3.5
		Refined Greedy	26,720	22	132,720	80 iterations of adjustment	5.08	12	13.62	8.2
		Enhanced SA	25,800	19	127,300	Convergence on 135	3.44	13.64	4.08	63.0

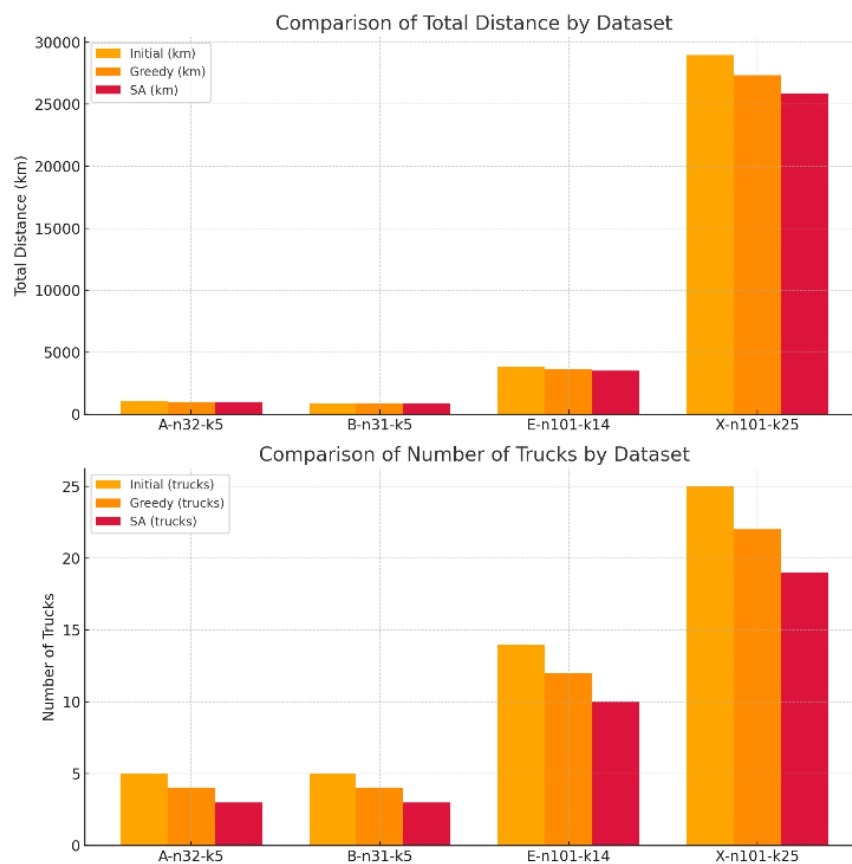


Figure 3. Comparative graph of total distance traveled and number of trucks required per dataset

5. DISCUSSION

In [25] they highlight the use of neighborhood operators and dynamic penalty structures to avoid premature convergence, thus diversifying searches, resulting in a cost reduction on average of about 5% compared to SA alone. In our research, this method was strengthened by applying adaptive temperature adjustment control strategies, operators have a weighted random weight and adding a penalty scheme for overload or overflow routes. In addition, integrated metrics have been included to simultaneously evaluate total route distance, number of trucks used and penalty costs, thus providing a better assessment of logistics performance. This combination of these factors allows exploring solutions in addition to local improvement and improving the final quality compared to the traditional SA and the GLS-SA framework installed in [25]. Therefore, our proposal provides a great added value, which provides a strong and flexible approach that is likely to be applied to major problems and logistic complexity.

In comparison with paper [11], which shows an SA algorithm for routing problems with two-dimensional load constraints, it is seen that, although it covered the challenge of spatial complexity, its focus lay in handling geometric and load constraints. Our proposal, despite capacity constraints, addresses distance and fleet minimization equally, and by using an adjustable penalty system on vehicle surpluses. The introduction of multiple operators and temperature adaptability ensure a more flexible adaptability, which puts us in an advantageous position.

Comparing with paper [15], Comparing with the article [15], which addresses the solution of a periodic capacitated routing problem using the SA technique, it should be noted that this research is focused on the exercise of delivering loads over several periods with higher rank in the stability and repeatability of routes. In contrast, our proposal focuses on the treatment of static instances, but with more restriction in the optimization of the margin of distance, number of vehicles and costs in each iteration in the solution. Also, we consider the use of validity control methods of the solutions, which are automatic and adaptive in the parameters and neighborhood selection, which makes it possible to deal with variability and avoid getting trapped in local optima. The differentiation lies in the possibility of calculating the cost of fleet overruns and punishing with step-type penalties, which gives more freedom to implement in environments with limited resources and unstable demand.

In [25], researchers addressed the planning of distribution routes for 26 fishing vessels located in the National Fishing Port of Moluccas, taking into account the attributes of distance, vessel capacity, catch volume, time and operating costs. The study applies GLS and SA developed in Google OR-Tools. The research shows that, with two or three vessels, the distances are similar to 290 and 355 miles. But when using four ships, the distance obtained by GLS is 464 miles, while SA achieves it in 439 miles, giving a 6% increase in efficiency. This difference shows that, when the problem is more complex, SA becomes more effective and manages to minimize distance, time and costs. In our research, we have used the SA algorithm but modified it to handle additional temporal dimensions and operational constraints such as time windows, capacity constraints, and load returns. By subjecting it to 200 test instances, we obtained on average a 10.07 % improvement in route distribution and customer service, confirming the robustness and optimization capability of the proposed approach in highly complex logistics scenarios.

6. CONCLUSION

The present study has demonstrated the effectiveness of heuristic and metaheuristic approaches in the optimization of the constrained VRP. The combination of the Greedy and SA algorithms allows obtaining efficient solutions, significantly reducing the total distance traveled, the number of trucks used and the associated penalized cost in the VRP. Given an initial solution, the Greedy algorithm significantly reduced the distance, number of trucks and penalty cost, and when the SA algorithm was applied, the distance, number of changes and penalty costs were further reduced, demonstrating that a combination of these algorithms could be used to achieve more robust and stable solutions compared to conventional methodologies. In terms of impact, cost reduction and better utilization of available resources represent substantial benefits for goods distribution management. This study lays the groundwork for future research in the integration of other advanced metaheuristic approaches and the incorporation of dynamic constraints in route planning, with the aim of further improving efficiency in logistics and transportation.

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DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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