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OPTIMIZATION OF VEHICLE ROUTING PROBLEM IN LOGISTICS USING GENETIC ALGORITHM

Research paper

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Abstract: Efficient vehicle routing is essential for reducing transportation costs and improving delivery performance in logistics. This paper presents a modified Genetic Algorithm (GA) for solving the Capacitated Vehicle Routing Problem (CVRP). The method combines tournament selection, order crossover, relocation mutation, elitism, and a best-improvement 2-opt local search procedure. The algorithm is evaluated on the E-n23-k3 benchmark instance, which consists of 22 customers, three vehicles, and a vehicle capacity of 4500. Twenty independent runs are performed, and the solutions are assessed using the best and average total distance, standard deviation, convergence behavior, and execution time. The algorithm obtained the benchmark solution in 18 of 20 runs, with an average distance of 570.74, a standard deviation of 4.44, and an average execution time of approximately 15 s. Since the study considers only one small benchmark instance, the results demonstrate the feasibility of the proposed approach but do not allow general conclusions regarding scalability. Further evaluation on larger and more diverse instances is required.
Key words: vehicle routing problem, logistics, optimization, genetic algorithm

INTRODUCTION

Supply chain management and logistics depend on efficient transportation planning to reduce costs, improve delivery reliability, and increase the responsiveness of distribution systems. Transportation planning is commonly formulated through combinatorial optimization problems such as the Traveling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP). While the TSP determines a minimum-distance tour for visiting a set of locations, the VRP extends this problem to a fleet of vehicles serving multiple customers under operational constraints (Laporte, 2007; Toth & Vigo, 2014).

This study focuses on the Capacitated Vehicle Routing Problem (CVRP), in which each customer must be visited exactly once and the total demand assigned to each vehicle must not exceed its capacity. The objective is to minimize the total travel distance. Because the search space grows rapidly with the number of customers and constraints, exact methods may become impractical for larger instances. Consequently, heuristic and metaheuristic methods, including Genetic Algorithms (GAs), are frequently used to obtain high-quality solutions within acceptable computational time (Braekers et al., 2016; Zhang et al., 2022).

This paper presents a modified GA for the CVRP. The proposed method combines tournament selection, order crossover, relocation mutation, elitism, and a best-improvement 2-opt local search procedure. Its performance is evaluated on the E-n23-k3 benchmark instance using 20 independent runs. The analysis considers the best and average solution values, standard deviation, convergence behavior, and computational time.

CAPACITATED VEHICLE ROUTING PROBLEM

The classical CVRP will be presented using the mathematical model (Zhang et al., 2022). CVRP can be defined as the problem where *n* vehicles operate from a central depot (node 0) to serve *m* customers, ensuring that vehicle capacity constraints are met. The objective is to determine a set of routes that minimizes the total travel distance or cost of all vehicles, subject to the following constraints (Borčinová, 2017):

- Each route must start and end at a central depot.
- Each customer is visited exactly once.

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- The total demand per route must not exceed the vehicle's capacity.

In the following mathematical expressions, d_i presents the demand of the customer *i*, u_s is the load of the vehicle *s*, while x_{ij}^s is the binary variable that does the following:

$$x_{ij}^s = \begin{cases} 1, vehicle\ s\ serves\ customer\ i\ followed\ by\ customer\ j \\ 0, else \end{cases}$$

The objective function is to minimize the total transportation cost for the entire fleet of vehicles which is mathematically defined as:

$$Cost = Minimize \sum_{s=1}^{n} \sum_{i,j=0}^{m} c_{ij} x_{ij}^s \quad (1)$$

where c_{ij} is the transportation cost from customer *i* to customer *j*. In other words, c_{ij} is cost or distance of travelling from node *i* to node *j* in the graph.
The objective function is followed by four different constraints that ensure the feasibility of the CVRP. The first constraint ensures that each vehicle starts from the depot and returns to the depot after delivering goods to the customers:

$$\sum_{j=0}^{m} x_{0j}^s = \sum_{j=0}^{m} x_{j0}^s = 1\,, s \in (1,2,\dots,n) \quad (2)$$

The second and third constraints are similar to one another and indicate that each customer, *i* or *j*, is visited only once. These constraints ensure vehicles do not reach a single customer twice, therefore maintaining a valid route structure:

$$\sum_{s=1}^{n} \sum_{\substack{j=0 \\ j \neq i}}^{m} x_{ij}^s = 1\,, i \in (1,2,\dots,m) \quad (3)$$

$$\sum_{s=1}^{n} \sum_{\substack{i=0 \\ i \neq j}}^{m} x_{ij}^s = 1\,, j \in (1,2,\dots,m) \quad (4)$$

This last constraint ensures that the total demand served by each vehicle does not exceed its maximum load capacity:

$$\sum_{i=1}^{m} d_i \sum_{\substack{j=0 \\ i \neq j}}^{m} x_{ij}^s \leq u_s\,, s \in (1,2,\dots,n) \quad (5)$$

METAHEURISTIC ALGORITHMS

Metaheuristics are high-level optimization methods designed to explore large and complex search spaces. They combine global exploration with local exploitation and are particularly suitable for NP-hard problems for which exact methods may require excessive computational time (Blum & Roli, 2003; Talbi, 2009). In VRP applications, frequently used metaheuristics include genetic algorithms, tabu search, simulated annealing, and ant colony optimization.
A Genetic Algorithm represents candidate solutions as chromosomes and improves a population through selection, crossover, mutation, and replacement. In this study, GA was selected because its population-based search is suitable for exploring alternative vehicle

sequences and route assignments. A 2-opt local search procedure was additionally incorporated to improve individual routes.

MATERIALS AND METHODS

To address the outlined research questions from the previous chapter and evaluate the effectiveness of the proposed genetic algorithm (GA), a structured methodological approach has been adopted. This includes selecting a representative benchmark instance of the Capacitated VRP (CVRP), implementing a modified GA with integrated local search heuristic, and systematically analyzing the algorithm's performance across multiple runs. By employing a standardized problem instance, the study ensures result comparability and allows for a precise assessment of the GA's ability to approach or reach the known global optimum. Furthermore, detailed attention is given to the algorithm's components, such as tournament selection, order crossover, relocation mutation, and 2-opt local search heuristic in order to investigate their individual and collective impact on solution quality and convergence behavior.

Benchmark problem instance

A benchmark problem instance is selected from the CVRP repository available at http://vrp.atd-lab.inf.puc-rio.br/index.php/en. This repository provides a wide range of CVRP instances, each varying in complexity based on the number of customers and vehicles. It includes benchmark sets dating from 1969 to 2011. For this study, the ***E-n23-k3*** instance from Set E (Christofides & Eilon, 1969) is used. This instance consists of 22 customers, served by three vehicles, each with a capacity of 4500. Both the customers and the depot are represented by x- and y-coordinates, enabling the calculation of Euclidean distances between locations. Their coordinates are graphically presented on the map in Figure 1. The global optimum for this instance is 569 in terms of total travel distance.

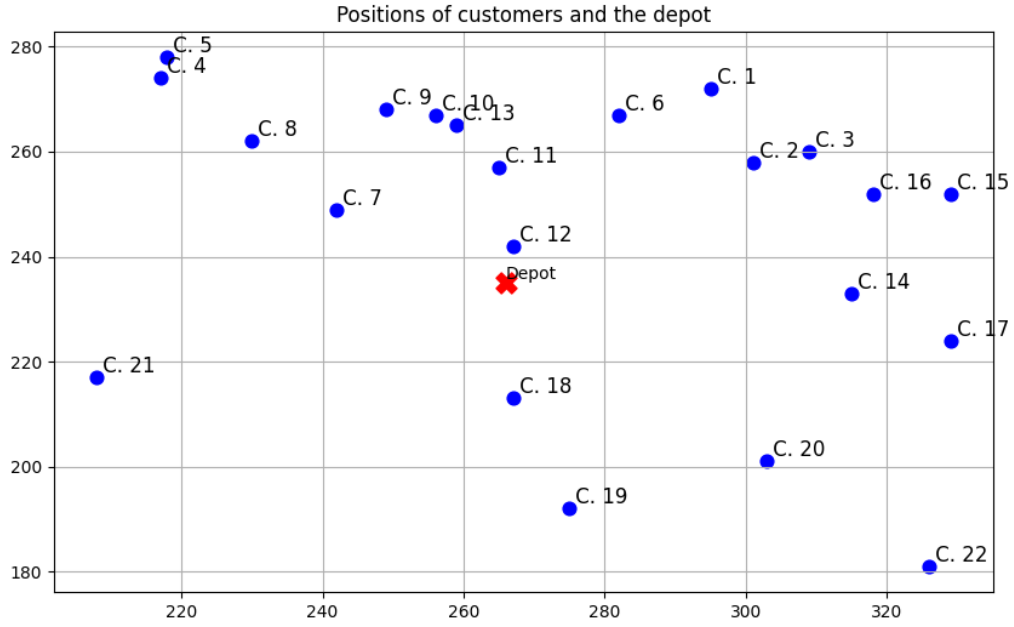


***Fig. 1**. Coordinates of customers and the depot for the instance E-n23-k3*

Genetic algorithm for CVRP

The proposed GA represents each solution as a customer sequence together with its division into vehicle routes. The initial population consists of feasible solutions. The fitness value is defined as the total Euclidean travel distance, including the return from each route to the depot.

Tournament selection with a tournament size of five is used to select parent solutions. Order crossover (OX) preserves customer uniqueness, while relocation mutation moves a customer between routes when the capacity constraint remains satisfied. A best-improvement 2-opt procedure is then applied to improve individual routes. Elitism preserves the best solutions between generations, and the algorithm is terminated after 500 generations. Infeasible solutions are repaired or rejected during the solution-generation process. The flowchart of the proposed GA for CVRP problem is given in Figure 2.

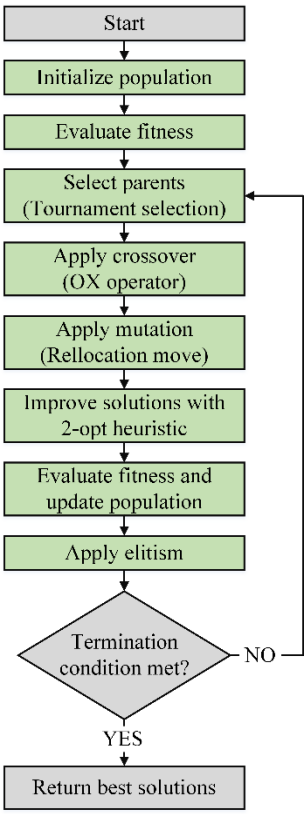


***Fig. 2**. Flowchart of GA for CVRP*

RESULTS AND DISCUSSION

The proposed GA was implemented in Python and evaluated in 20 independent runs on a laptop equipped with a 13th Generation Intel Core i7-13650HX processor and 16 GB of RAM. The best solution obtained a total distance of 569.59, while the average distance over all runs was 570.74, with a standard deviation of 4.44. The best result was obtained in 18 of the 20 runs. The average execution time was approximately 15 s per run. The optimal distance and optimal vehicle routes are presented in Tables 1 and 2. The graphical presentation of the optimal vehicle route for "E-n23-k3" CVRP problem instance is shown in Figure 3.
All three vehicle routes satisfied the capacity constraint of 4500. The loads were 4389, 4325, and 1400, respectively. The utilization of vehicles is shown in Table 3. The relatively uneven load distribution is a consequence of distance minimization and does not necessarily indicate a deficiency of the algorithm, since balanced vehicle utilization was not included as an objective.

***Table 1**. Optimal total distance with respect to capacity limit*

Optimal distance	Average distance	Standard deviation
569.59	570.74	4.44

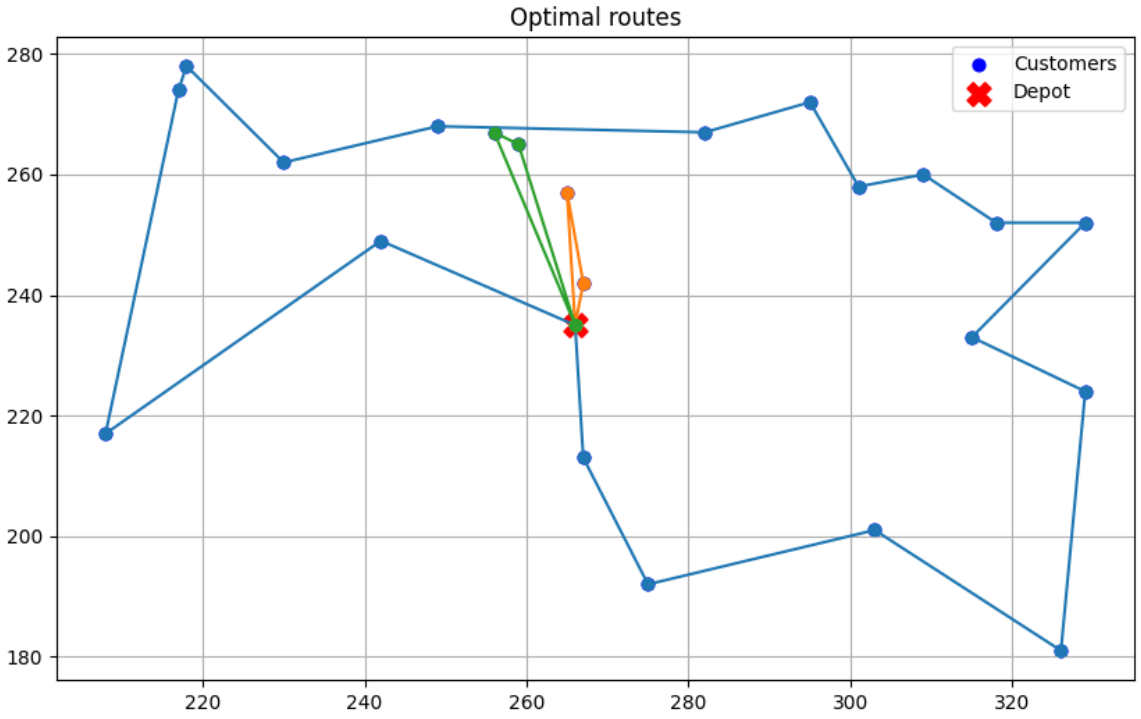


***Fig. 3**. The optimal vehicle routes for the CVRP instance E-n23-k3*

***Table 2**. The optimal vehicle routes*

Vehicles	**Optimal vehicle routes**
Vehicle 1	[0-7-21-4-5-8-9-6-1-2-3-16-15-14-17-22-20-19-18-0]
Vehicle 2	[0-11-12-0]
Vehicle 3	[0-10-13-0]

***Table 3**. Utilization of each vehicle*

Vehicle	Route load	Capacity	Utilization
Vehicle 1	4389	4500	97.53%
Vehicle 2	4325	4500	96.11%
Vehicle 3	1400	4500	31.11%

The convergence curve shows a rapid improvement during the initial generations, followed by stabilization of the best-so-far solution. Figure 4 shows the convergence curve for this problem instance. This behavior indicates that the combination of tournament selection, elitism, and 2-opt local search effectively accelerates local route improvement. However, the convergence plot represents one run and should not be interpreted as a complete statistical analysis of convergence across all 20 runs.

In the additional operator comparison, removing the 2-opt procedure increased the average distance by approximately 7% under the same experimental settings. This result suggests that local search contributes substantially to the quality of the final routes. Nevertheless, the comparison should be supported by a separate table containing the mean value, standard deviation, and number of runs for each algorithmic variant.

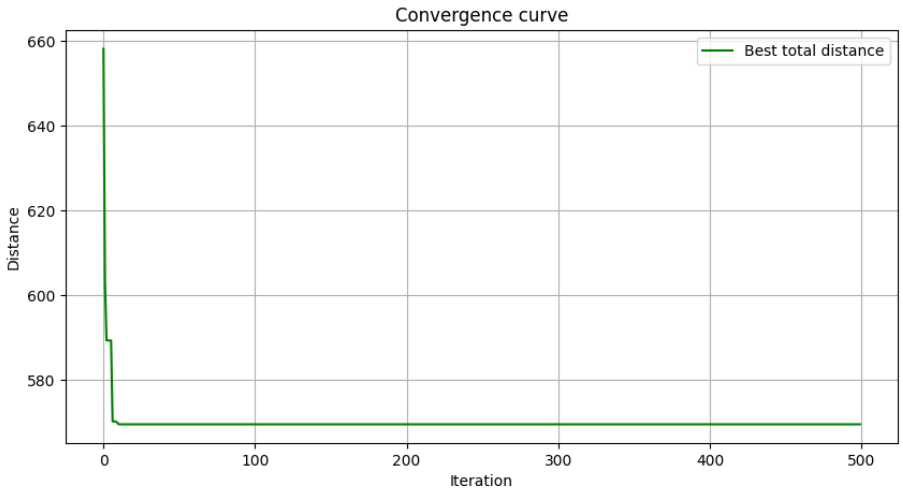


***Fig. 4**. Convergence curve of the proposed GA*

In order to evaluate the contributions of various operators within the proposed GA, controlled experiments were conducted to quantify the impact of the tournament selection OX crossover, relocation mutation, and 2-opt heuristic on the quality and stability of the obtained solutions. The results indicate that each of the analyzed operators has a specific and significant contribution, both in terms of minimizing the total distance traveled and in ensuring the robustness and stability of the algorithm across multiple runs.

The analysis of tournament selection showed that tournament size significantly influences the balance between exploitation and exploration: larger tournaments accelerate convergence but at the cost of potential premature convergence, while smaller tournaments allow diversity but with slower solution improvement. The optimal value in the study was found to be a medium-sized tournament (n=5), which provides a good compromise between solution quality and stability.

An additional operator analysis showed that the combined GA structure performed better than variants without the considered operators. Removing the 2-opt procedure increased the average distance by approximately 7%, indicating its importance for local route improvement. Tournament selection with size 5 provided a suitable balance between convergence speed and population diversity. Relocation mutation improved route flexibility by allowing customers to be reassigned between vehicles while respecting capacity constraints..

CONCLUSION

This study presented a modified Genetic Algorithm for solving the Capacitated Vehicle Routing Problem. The algorithm combines tournament selection, order crossover, relocation mutation, elitism, and a 2-opt local search procedure. Tested on the E-n23-k3 benchmark instance with 22 customers and three vehicles, the algorithm reached the known optimum of 569.59 in 18 of 20 runs. The average solution value was 570.74, with a standard deviation of 4.44 and an average execution time of approximately 15 s.

The results confirm that the proposed GA can efficiently solve the selected small CVRP instance and consistently produce high-quality solutions. However, because the evaluation was conducted on only one benchmark instance, the findings cannot be generalized to larger or more complex logistics problems. Future work should include multiple benchmark instances, real-world data, time windows, dynamic demand, heterogeneous fleets, and comparisons with other metaheuristic methods.

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