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Optimizing Multi-Depot Vehicle Routing: An ABC-GA Hybrid Algorithm

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ABSTRACT

The Multi Depot Vehicle Routing Problem (MDVRP) is a generalized form of the Vehicle Routing Problem (VRP) and Travelling Salesman Problem (TSP). It is considered one of the NP-hard optimization problems. The MDVRP is a logistics problem that involves finding the most efficient route to transport goods between multiple different pickup and delivery locations. In this study a hybrid metaheuristic algorithm that integrates artificial bee colony and genetic algorithms is developed to solve MDVRP efficiently. The main objective of this study is to find the optimal route from multiple depots to serve a set of customers dispersed in different geographical locations. Initially nearest neighbor algorithm is used to assign customer to their nearest depot and randomly generated initial solution. These solutions are subsequently optimized using the proposed hybrid ABC-GA algorithm. The ABC algorithm serves as the main optimization framework, within which GA operators are embedded in the employed and onlooker bee phases. A probabilistic selection mechanism dynamically applies ABC neighbor search, GA operators, and 2-opt local search to improve solution quality. Finally, the results of the ABC-GA approach are compared against the outcomes of the conventional GA and ABC algorithm to assess performance improvements. Experimental results demonstrate that the hybrid approach consistently produces lower routing costs, achieving superior solution quality at the expense of increased computational time.

Keywords: MDVRP, ABC-GA, Artificial Bee Colony (ABC), Genetic Algorithm (GA), Route Optimization, Metaheuristics

1. Introduction

The vehicle routing problem (VRP) is a logistics and combinatorial optimization problem that involves finding the best routes for vehicles over a network. It is used in logistics for the transportation and distribution of goods. For MDVRP goods are served from multiple depots to customers. MDVRP is an NP hard problem where the optimization difficulty increases as the number of customers or depots grows.

Mathematically MDVRP expressed as given m depots and n customers, a certain number of vehicles is assigned to each depot. The vehicles depart from the depots to deliver goods to customers, complete the service, and then return to the depots. The objective is to plan the optimal delivery routes to minimize the total transportation cost. This problem can be represented by a directed graph $G = (V, E)$, where V is the set of nodes, including m depot nodes and n customer nodes. $E = \{(i,j) | \, i,j \in V, i \neq j\}$ is the set of all possible routes for i node to j node and each edge is associated with the a cost d_{ij}. $x_{i,j,k} = 1$ if vehicle k travels directly from i to j otherwise 0. The goal is to assign each customer to exactly one depot and find routes for vehicles starting and ending at their assigned depots that minimize the total cost.

$$\text{Minimize cost} = \sum_i \sum_j \sum_k d_{ij} \times X_{ijk} \quad (1)$$

Problem is solved under following constraints:

- Each customer is visited only once by a vehicle
- Each vehicle must start and end its route at the assigned depot

This problem is economically important as optimization of the routes and proper depot management can lead to a significant cost saving by finding most efficient routes which will minimizes fuel consumption and other maintenance and labor cost associated with the transportation. Different methods have been developed to solve VRP problems such as exact method, heuristic method. Exact optimization techniques such as Mixed-Integer Programming guarantee optimality but become computationally infeasible for large MDVRP instances. Metaheuristic approaches such as Genetic Algorithms (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC) algorithms can produce high-quality solutions within reasonable time. Each method has own limitations for instance ABC algorithms better at global exploration [1] but may lack in local refinement, while GA offers strong local exploitation but risks premature convergence[2, 3]. Hybrid metaheuristics combine the strengths of multiple algorithms to balance exploration and exploitation more effectively. Insufficient amount of prior work has integrated ABC and GA for solving this problem. To the best of our knowledge, the proposed hybrid framework is a novel hybrid framework integrating ABC, GA, and 2-opt in a probabilistic multi-operator structure. The main contribution of this study is the development of a

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hybrid framework integrating ABC and GA with 2opt local search and studying how algorithms perform with varying customer and depots.

2. Literature Review

In this section existing work on the Multi-Depot Vehicle Routing Problem (MDVRP) using metaheuristic algorithm is briefly discussed. Comert et al. 2023[4] suggested HACO-ABCA, a hierarchical hybrid combining Ant Colony Optimization (ACO) and Artificial Bee Colony Algorithm (ABCA), which outperformed competing methods on benchmark instances. Gu et al. 2022[5] proposed a coevolution strategy to depot combination within an ABC framework where depot clustering is used to convert the MDVRP to simple VRP. Then we modify the ABC algorithm for single-depot VRP to generate solutions for each depot. Peng et al. 2020[6] suggested a hybrid evolutionary algorithm combining variable neighborhood search, using a route-based crossover operator and a multi-criteria population update strategy; their results showed superiority over the exact solver CPLEX. Davoodi et al. 2019[7] investigated an ABC–GA hybrid for VRP, noting the critical role of scout bee generation in determining solution quality. Rabbani et al. 2018[8] reported that a hybrid GA outperformed standard GA in MDVRP with time windows and mixed pickup/delivery operations. Zhong et al. 2017[9] demonstrated that ABC-GA provided stable and efficient performance compared with ALNS and GRASP+VND on 93 test problems. Zhang et al. (2014) integrated genetic crossover technique directly into the ABC framework. Geetha et al. 2012[10] merged GA and PSO for MDVRP, employing clustering-based initialization and local search refinement. Surekha et al. 201[11] used GA with Clarke and Wright savings for route generation, and Chen et al. 2008[12] confirmed the feasibility of hybrid metaheuristics for MDVRP.

3. Methodology

3.1 Data Collection

Data are collected from Kaggle data set[13]. Data should contain multiple depot location, customers locations and total number of customers.

3.2 ABCGA Algorithm

The proposed framework consists of two metaheuristic algorithms one is ABC which is based on foraging behavior of honey bees another is GA which is based on Darwin's evolution theory and mimics human evolution and breeding. The employed bee phase implements a multi-strategy selection mechanism that combines three distinct optimization operators: GA, ABC neighborhood search, 2-opt local search. Each employed bee corresponds to a food source (solution) and applies one of these operators based on a probabilistic selection scheme.

Step 1: Customer and depot data loaded and computed a distance matrix using equation (2) and stored the cost between every pair of the node.

$$\text{Distance, } d_{ij} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \quad (2)$$

Step 2: Customer depot assignment
Customers are assigned to the nearest depot and one vehicle is allocated to each depot.

Step 3: Initial population generation
Initial population is generated by assigning customer to vehicle route by random permutation of customer sequence for each depot as shown in Fig. 1. Each solution has a probability to be potential solution to the optimization problem. Fitness is evaluated based on the fitness function (eq. 3).

$$\text{Fitness} = \frac{1}{1+\sum d_{ij}} \quad (3)$$

Fig. 1 Random initial solution

Step 4: Employee Bee Phase: Employed bee modifies its current solution by applying one of the following algorithms.

3.2.1 Genetic Algorithm

Two major features of genetic algorithm are used, which are
Crossover Operation: The Order Crossover (OX) is employed to combine two parent solutions while preserving the relative order of customers. Crossover technique involves combining two best solutions to create new offspring having variation.
Mutation Operation: Two types of mutation operators are implemented:
Swap Mutation: Swaps two randomly selected customers as shown in Fig. 2.

Fig. 2 Swap operation

Insert Mutation: It relocates a customer to a different position. For example (Fig. 3), customer C5 inserted in the position of C2 in a solution.

Before Insertion [D1, C1, C2, C3, C4, D1]
After Insertion [D1, C1, C5, C3, C4, D1]

Fig. 3 Insertion mutation

3.2.2 ABC Neighborhood Search

ABC neighborhood search employs two types of neighborhood operations:
Random Swap: Randomly selects two customers within a depot's route and swaps their positions.
Random Insert: Removes a customer from its current position and inserts it at a randomly selected position within the same depot's routes.

3.2.3 2 Opt Local Search

It improves route structure by changing two non-adjacent edges of the routes.

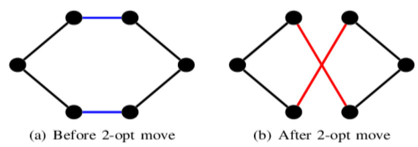

Fig. 4 2-opt local search

3.2.4 Onlooker Bee Phase

In this phase onlooker bees select food sources based on their fitness quality using roulette wheel selection. The selection probability is proportional to the fitness value of each solution. Higher the fitness the more is likely to be selected and modified further using ABC neighborhood search, GA, and 2 opt local search. The probability-based selection process evaluated by equation (4).

$$P_i = \frac{\text{Fitness}}{\sum_{i=1}^{N} \text{Fitness}} \quad (4)$$

This ensures that better solutions are given higher preference, leading to a more focused search around high quality solutions.

3.2.5 Scout Bee Phase

If a solution has not improved for a predefined number of iterations, the scout bee replaces the stagnated solution with a randomly generated new solution.

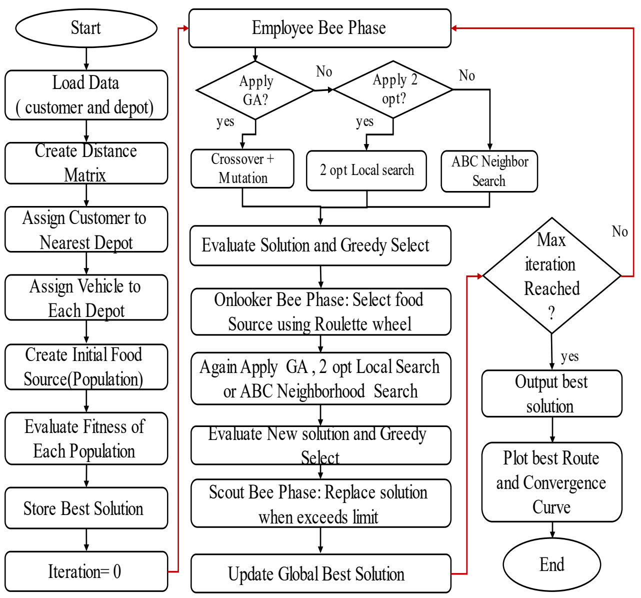

Fig. 5 Flow chart of the MDVRP

4. Experimental Setup and Results

The proposed hybrid ABC-GA algorithm was implemented in Python and evaluated on datasets obtained from Kaggle. Experiments were conducted on a system with an Intel® Core™ i5-10300H processor (2.50 GHz) and 8 GB RAM. The algorithm was executed with a colony size of 50 bees and a maximum of 500 iterations. Nine problem instances were considered, with the number of customers ranging from 50 to 249 and the number of depots varying between 2 and 6. The performance of the proposed method was compared with standalone GA and ABC algorithms, and the results are presented in Table 1.

Table 1 Problem solution with Corresponding optimized cost and time

Problem	Customer (depot)	Framework	Cost	Time (second)
1	50(4)	ABC-GA	**476.13**	**19.45**
		GA	492.62	29.57
		ABC	498.96	14.61
2	75(5)	ABC-GA	**593.02**	**36.11**
		GA	611.99	41.85
		ABC	619.78	38.56
3	100(2)	ABC-GA	**656.58**	310.71
		GA	732.64	21.06
		ABC	984.02	21.93
4	100(3)	ABC-GA	**663.89**	158.05
		GA	775.68	14.52
		ABC	914.88	27.79
5	100(4)	ABC-GA	**701.52**	91.11
		GA	821.52	18.98
		ABC	882.06	34.71
6	249(4)	ABC-GA	**2533.98**	1171.01
		GA	3903.52	66.44
		ABC	6256.33	46.56
7	249(6)	ABC-GA	**2631.10**	746.24
		GA	4740.59	48.85
		ABC	6492.83	60.05
8	80(2)	ABC-GA	**1280.83**	158.97
		GA	1553.24	10.35
		ABC	2206.09	20.56
9	240(6)	ABC-GA	**3913.44**	483.77
		GA	5939.01	46.4
		ABC	8328.59	57.90

Problem Set 1:

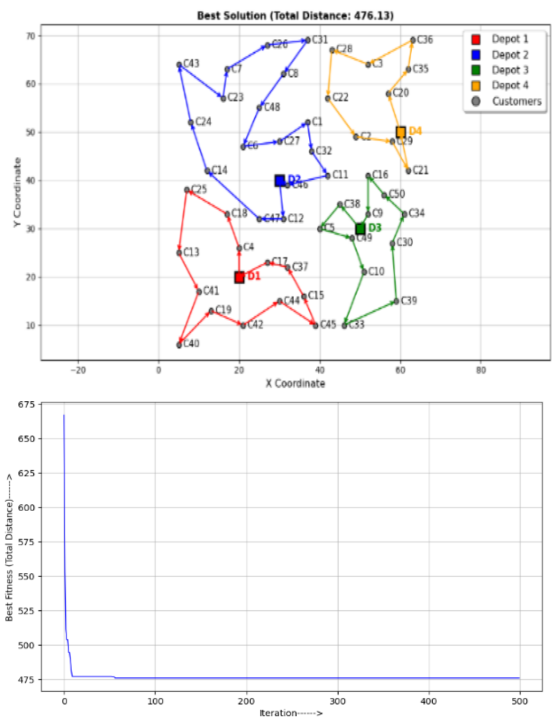

Fig. 6 Optimized route and algorithm convergence curve for problem 1

Problem Set 2:

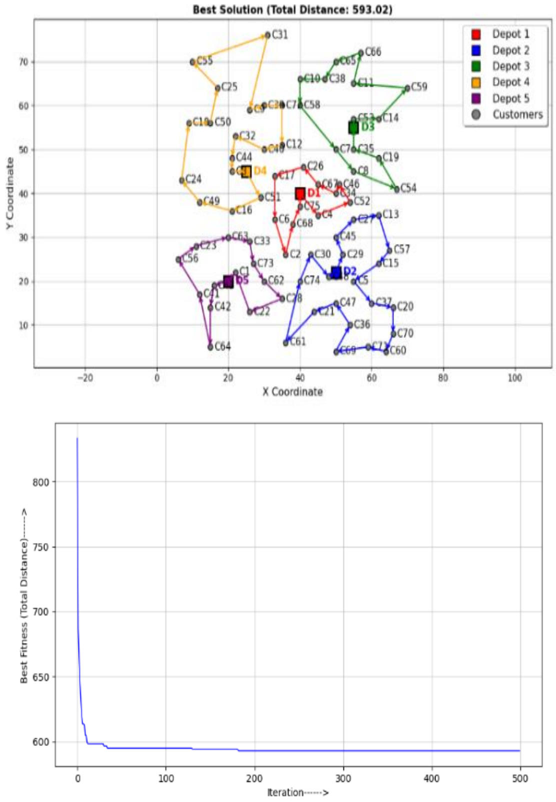

Fig. 7 Optimized route and algorithm convergence curve for problem 2

Problem Set 3:

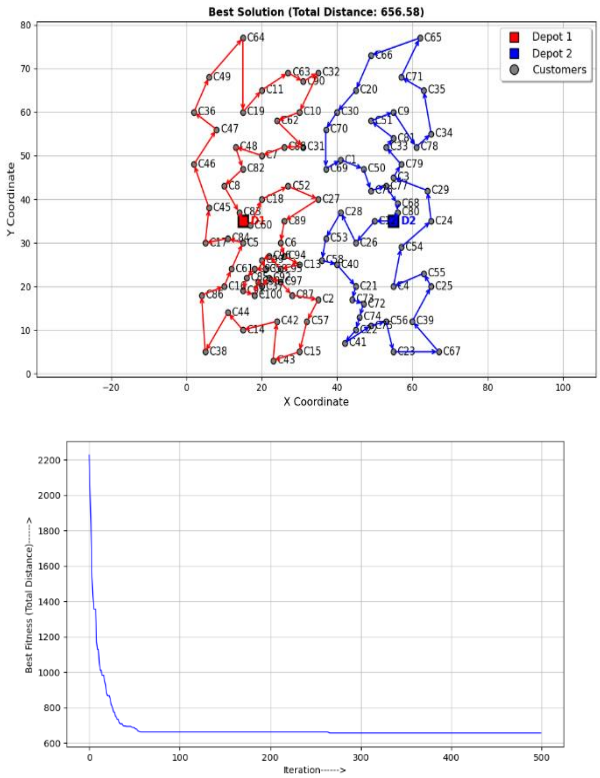

Fig. 8 Optimized route and algorithm convergence curve for problem 3

Problem Set 4:

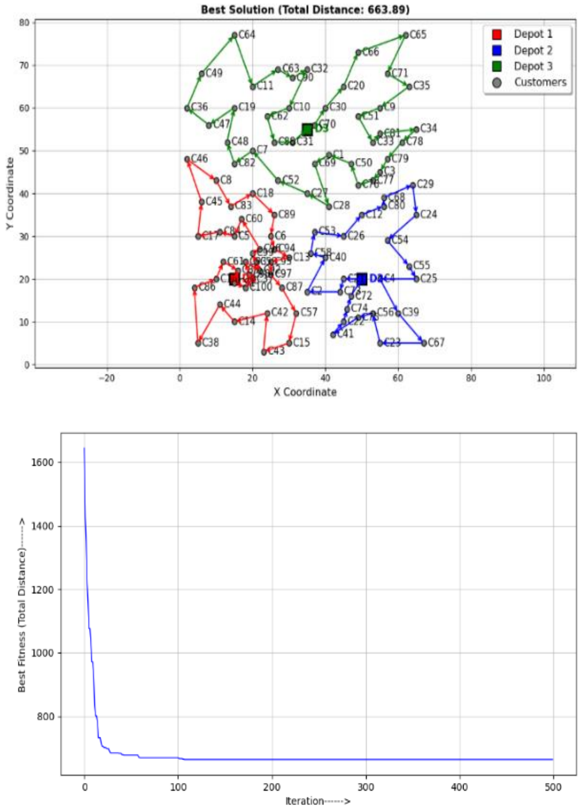

Fig. 9 Optimized route and algorithm convergence curve for problem 4

Problem Set 5:

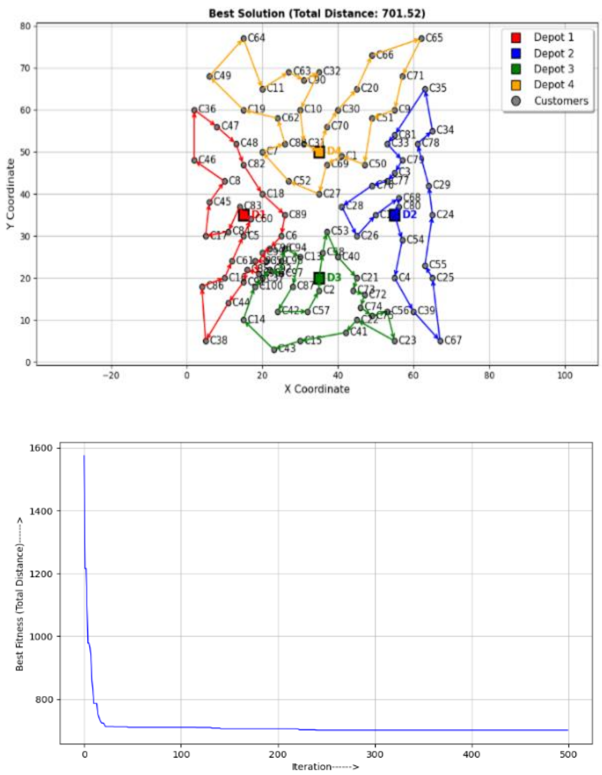

Fig. 10 Optimized route and algorithm convergence curve for problem 5

Problem Set 6:

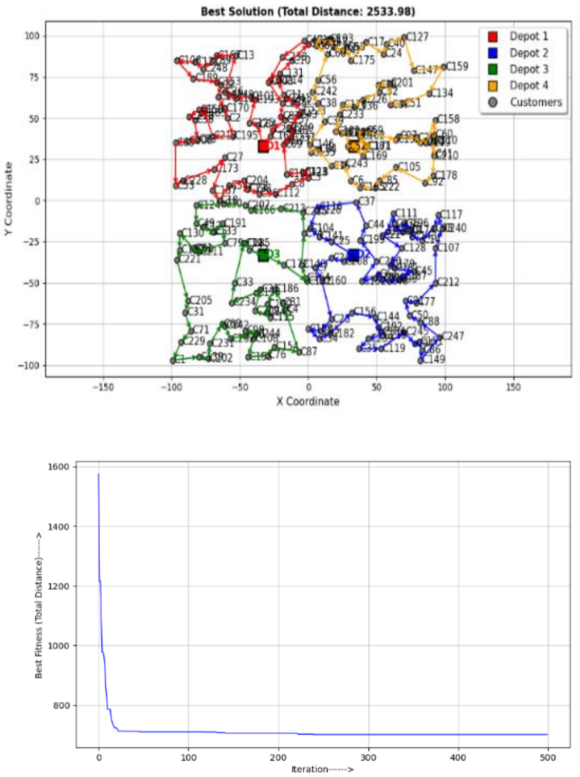

Fig. 11 Optimized route and algorithm convergence curve for problem 6

Problem Set 7:

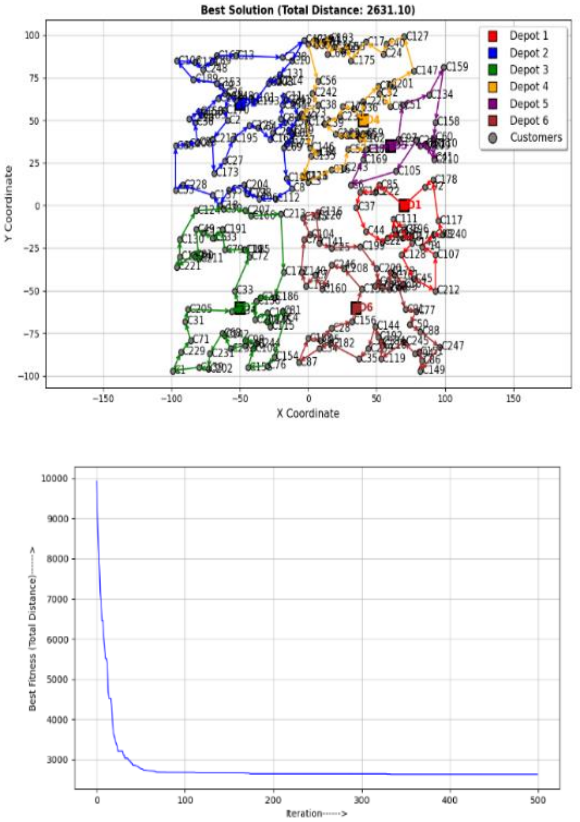

Fig. 12 Optimized route and algorithm convergence curve for problem 7

Problem Set 8:

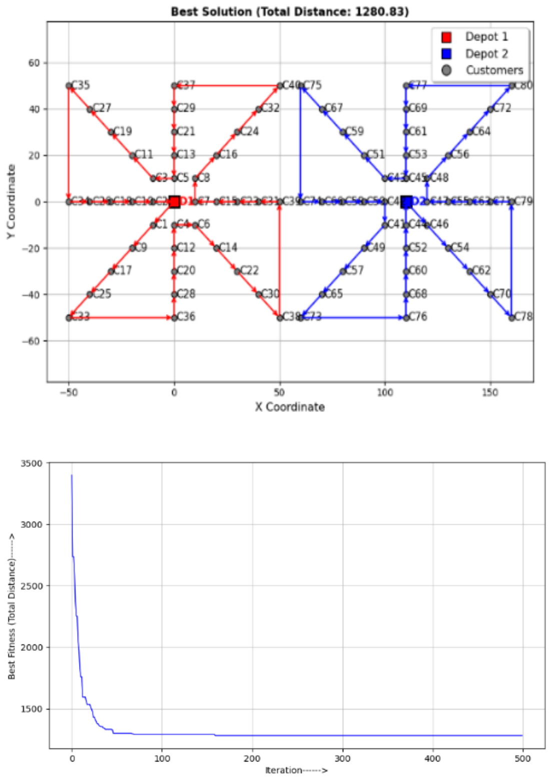

Fig. 13 Optimized route and algorithm convergence curve for problem 8

Problem Set 9:

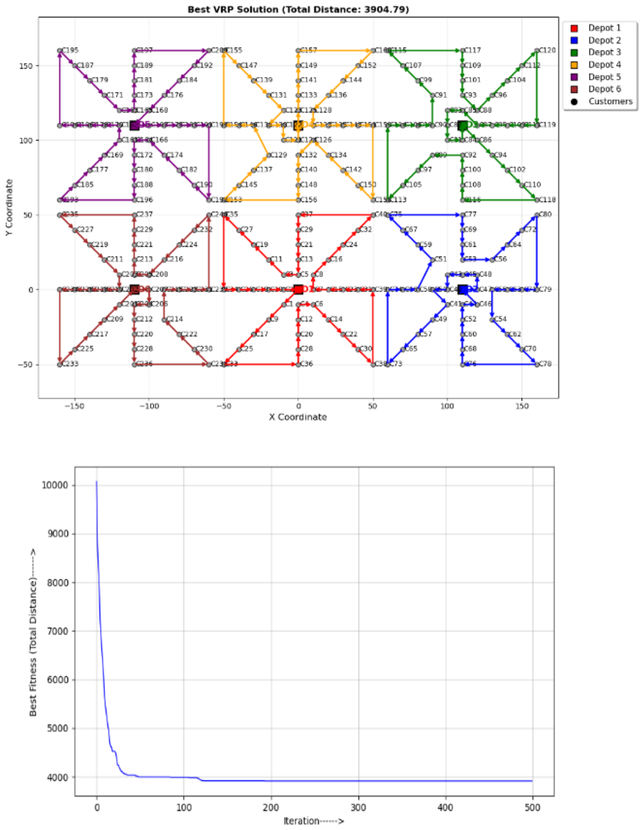

Fig. 14 Optimized route and algorithm convergence curve for problem 9

From the convergence curve (Fig. 6 to 14) of ABC-GA of each problem execution, it is clear that most improvement occurs in the early stage of the iteration with diminishing gain toward end. The results show that the ABC-GA hybrid consistently produces the lowest route cost, outperforming both GA and ABC across all problem sizes (Fig. 15). However, this improvement comes at the cost of significantly higher computation time, especially for large datasets. GA offers moderate performance, while ABC is fastest but delivers the poorest cost. Overall, the hybrid algorithm provides the best optimization quality, showing a clear tradeoff between solution accuracy and runtime.

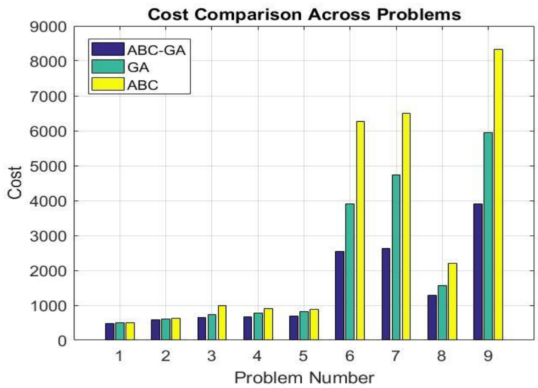

Fig. 15 Cost comparison of algorithms with different problem size

5. Conclusion

The main focus of this study is to implement a hybrid algorithm integrating ABC and GA to find solution of Multi-Depot Vehicle Routing and analyzing the algorithm performance on different problem size. For smaller instances (50–100 customers), the algorithm achieved low-cost solutions within short computation times, highlighting its efficiency. In larger instances (≥100 customers), execution time increased as expected due to problem complexity, but solution quality remained strong, indicating robustness and scalability.

6. Future Work

Although the proposed algorithm demonstrates strong performance across problem instances of varying sizes, there remain several opportunities for further improvement. Future work may extend the algorithm to more complex variants of the Vehicle Routing Problem, such as the capacitated VRP and the VRP with time windows. Additionally, the framework can be adapted to address dynamic MDVRP scenarios and enhanced through systematic algorithm parameter tuning.

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