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A Hybrid Approach for Solving the Capacitated Vehicle Routing Problem

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Research Article

Abstract

Industrial transportation problems, such as the distribution of petroleum products, industrial gases, merchandise, and waste management, are critical challenges in operations research. These issues often involve high costs and complex logistics, making efficient solutions essential for businesses. The routing problem, a well-known optimization challenge, focuses on minimizing transportation costs while satisfying vehicle capacity. In this research, we propose an innovative approach Hybrid Artificial Bee Colony (HABC), which combines the Artificial Bee Colony (ABC) algorithm with the Genetic Algorithm (GA). The ABC algorithm is recognized for its rapid convergence, whereas GA is effective at diversifying the search space through genetic operators such as crossover and mutation. By integrating these two metaheuristics, HABC aims to exploit their complementary strengths, thereby improving both solution quality and computational performance. In addition, we introduce a heuristic for random population initialization, which ensure a balance between quality and diversity in the initial solutions. This strategy helps avoid premature convergence and explores a broader solution space. Simulation results demonstrate that HABC achieves significant improvement in solution quality, outperforming existing methods in several instances of the CVRP. This approach not only reduces transportation costs but also offers a scalable and efficient framework for solving complex industrial logistics problems. By optimizing routes and resource allocation, HABC contributes to more sustainable and cost-effective operations, offering tangible benefits to industries that depend on reliable transportation systems. The proposed method underscores the potential of hybrid AI techniques in addressing real-world operational challenges.

Keywords: Artificial Intelligence; Genetic operators; Random initialization; Transport

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1. Introduction

As a necessity for both individuals and businesses, logistics is the process that ensures the physical movement of goods. It includes all actions involving the transfer of unfinished, partially finished, or finished goods [1]. The transfer can happen between companies within the same manufacturing sector or across different industries. Additionally, it may go directly from producers to ultimate consumers, via distributors like the distribution of petroleum products, the distribution of industrial gases, the distribution of merchandise to companies or individuals, care service tours, sales tours, garbage collection, and disposal, etc., and frequently involve high costs. Logistics combines transport, handling, packaging, and all the physical, administrative, informational, and organizational operations [2]. It employs a range of techniques to deliver the customer with the desired goods at the lowest possible cost, within the requested timeframe and quantity.

This has encouraged us to propose a hybrid method for the Capacited Vehicle Problem (CVRP) with the aim of minimizing the total distance as well as the number of vehicles. Figure 1 illustrates an example of CVRP that includes:

- Depot, where each route departs from and ends at the depot,
- Clients whose are represented by nodes and each node is visited exactly once,
- Homogeneous vehicles, such that vehicle capacity is not exceeded, and the number of vehicles used is not greater than the number available.

Because the problem is NP-hard, this motivated us to move towards metaheuristic approaches. A variety of metaheuristic approaches have been suggested to solve optimization problems, such as the artificial bee colony approach, the ant colony optimization, the genetic algorithm, etc [3]. One of the most well-known evolutionary algorithms developed in 2005 by Karaboga, is the ABC metaheuristic [4]. The ABC presents many improvements compared to the previous population-based algorithms. Indeed, it utilizes fewer control parameters compared to other optimization algorithms, making it simpler to integrate with them. Additionally, it exhibits robustness and rapid convergence, while being user-friendly, highly adaptable, and efficient [5], [6], [7]. Nevertheless, the ABC algorithm has the disadvantage that sometimes the optimal value cannot be found because it easily falls into premature convergence in the later search phase [8].

The genetic algorithm ranks among the most effective methods to solve problems with high computational complexity, such as VRP [9], [10]. Indeed, the genetic algorithm is a key technology in random search to solve any problem that requires a significant amount of computing time to find the optimal solution [11].

Based on the advantages of the ABC method and the GA, this paper proposes a hybrid of the artificial bee colony algorithm and the genetic algorithm to solve the capacited vehicle routing problem. The principle of this hybridization is expected to provide better convergence and to solve the problem more effectively. The objective of combining ABC with GA is to achieve a better result, to combine their advantages, and to mitigate their limitations. The efficiency of the suggested method is evaluated using benchmark datasets.

The primary objective of this paper is to devise a discrete hybrid artificial bee colony optimization algorithm and apply it to the capacitated vehicle routing problem. We adopt an integer vector to represent solutions and introduce suitable crossover and mutation strategies within both the employed and onlooker bee phases. As a result, our contribution encompasses three aspects:

1. To exploit the robustness, rapid convergence and high flexibility of the ABC metaheuristic, which also has the advantage of requiring fewer control parameters.
2. To enhance the efficiency of the artificial bee colony metaheuristic, we propose hybridizing it with the genetic algorithm. This approach enables the diversification of solutions through various genetic operators, thereby preventing the algorithm from becoming trapped in local optima.
3. To carry out an experimental study to assess the efficiency of the proposed HABC algorithm and to analyze its performance when applied on well-known CVRP benchmark instances.

The rest of this paper is structured in seven parts. In Section 2, we present a concise review of the literature on CVRP. In Section 3, we explain our motivation. In Section 4, we define bio-inspired methods. Section 5 describes the proposed HABC algorithm. In Section 6, we present the results and discuss them. Section 7 outlines the limitations of the study. Finally, the conclusions of the study and suggestions for future work are presented in Section 8.

2. Motivation

Even though most of the existing methods, as discussed in the previous section, usually perform well in most of the cases where they are applied, there is still room for developing a hybridization of metaheuristics for the reason that the existing methods have some limitations, either in terms of computational time or applicability to different kinds of optimization issues [12]. For example, Altabeeb et al. [13] proposed integrating the Firefly Algorithm (FA) with two local search techniques, 2-opt and enhanced 2-opt, to accelerate convergence. Also, they incorporated crossover and two types of mutation operators in the genetic algorithm to maintain the diversity of the solutions and prevent the algorithm from converging prematurely to a local optimum.

Additionally, Nayyar et al. [14] studied the benefits of ABC in different optimization fields. The high convergence rate of ABC in different fields has motivated us to use ABC for CVRP. Also, GA gives a more diversified solution space due to its different genetic operators [15]. Thus, a hybridization of these two metaheuristics could be more efficient to solve the CVRP.

3. Literature Review

Because the CVRP presents a complex combinatorial optimization challenge, known to be NP-hard, the researchers focused on enhancing metaheuristics via employing novel mechanisms in order to generate solutions within the discrete search space. Metaheuristics are used because of their ability to address different optimization challenges and generate quality solutions for complex optimization problems in a reduced computational time.

For example, Zhang et al. [16] suggested a hybrid quantum evolutionary approach to treat the CVRP. According to their experimental findings, the hybrid quantum evolution algorithm outperformed the genetic algorithm and the particle swarm optimization method, Yu et al. [17] implemented an upgraded ant colony metaheuristic that used the 2-Opt method to improve the algorithm's performance. Zhao et al. [18] proposed a discrete invasive weed approach. They used real matrix real encoding, and a two-stage hybrid neighborhood search method to guarantee stability between global and local search capabilities to search for the best solution. Their experiments showed that the invasive weed approach outperforms quantum evolutionary, genetic, particle swarm optimization, and ant colony algorithms expressed in terms of performance calculation, convergence rate, and optimization efficiency. Goel et al. [19] developed a hybrid approach integrating the ant colony algorithm and firefly algorithm to treat the CVRP. They suggested a novel representation of firefly and a technique for measuring distances; and they demonstrated the superiority of their proposed approach compared to the existing firefly algorithm based approaches. Thammano et al. [20] suggested a combination of the ant method, a sweep method, and path relinking to resolve a CVRP problem.

Dalbah et al. [21] adapted the Coronavirus Herd Immunity Optimizer (CHIO), a metaheuristic algorithm inspired by COVID-19 herd immunity strategies, to address the CVRP. The adaptation involved modifying CHIO's operators to ensure feasible solutions for CVRP instances. The algorithm was tested on two datasets: ten Synthetic CVRP models and the ABEFMP dataset with 27 instances. The modified CHIO achieved comparable results with existing algorithms on the first dataset and ranked first in 8 out of 27 instances on the second, more complex dataset.

Recently, Kalatzantonakis et al. [22] suggested a reinforcement learning algorithm to determine which local search operators should be used in which order. They introduced a new hyper-heuristic model, named Bandit Variable Neighborhood Search, based on the Variable Neighborhood Search method, and improved it with a hyper-heuristic strategy derived from the Multi-Armed Bandit. Their results showed that the proposed Bandit learning procedures possess a small computation footprint and are easier to apply. Souza et al. [23] presented a hybrid approach using a discrete differential evolution metaheuristic associated with local search algorithms to resolve the CVRP. The outcomes they obtained indicated that the approach they proposed was significantly better than other methods used in the literature. Tiwari et al. [24] evaluated Tabu Search, and Local Search algorithms, which give a sub-optimal result to the greedy solution of the CVRP problem. They compared the solution provided by these algorithms to the optimal solution that can be achieved in exponential time. Their results showed that Tabu search outperformed the other techniques for large instances, but for small instances, local search can generate comparable results to Tabu search in significantly less time. Zhang et al. [25] integrated an artificial bee colony optimization with variable neighborhood search to address CVRP. By embedding multi-variable neighborhood operators into the local search phase, their algorithm improved solution diversity and stability, achieving superior performance compared to existing methods. Yong et al. [26] proposed an adaptive hybrid ant colony optimization algorithm, introducing adaptive mechanisms in pheromone updating and state transferring rules. By combining sub-route construction with genetic algorithms and local search techniques, their method enhanced optimization accuracy and efficiency in solving CVRP.

Several reviews have also enriched the field by classifying and synthesizing metaheuristic approaches. Elshaer and Awad [27] presented a detailed taxonomic review of metaheuristics for VRP and its variants, offering a structured perspective on algorithmic strategies and hybridizations. Similarly, Tan and Yeh [28] provided a broad classification of VRP problems and solution techniques, identifying current trends and research challenges.

Beyond review papers, specific hybrid and bio-inspired approaches have been proposed. For instance, Altabeeb et al. [29] developed a cooperative firefly algorithm tailored to CVRP, achieving competitive performance and fast convergence. Boğar and Beyhan [30] introduced a hybrid genetic algorithm to address the mobile robot path problem, highlighting the efficiency of combining traditional heuristics with nature-inspired techniques concepts relevant to CVRP solution development.

Other different extensions of routing problems are treated that consider environmental aspects, like Djebbar et al. [31] formulated a novel pickup and delivery problem with time windows that takes into account CO_2 emissions and proposes a hybrid discrete artificial bee colony algorithm to solve it. Sadati et al. [32] and Wen et al. [33] considered the multi-depot green vehicle routing problem.

4. Bio-inspired Optimization Methods

Bio-inspired optimization methods, including the Artificial Bee Colony (ABC) and the Genetic Algorithm (GA), have been widely developed. Karaboga [6] provided a comprehensive survey of these algorithms, highlighting their applications and the behaviors of bee swarms that inspired their development. Gao et al. [8] presented an improved version of the ABC algorithm, incorporating differential evolution and a new search mechanism. Pham et al. [34] introduced the Bees Algorithm, which mimics the foraging behavior of honeybees and has been shown to handle complex optimization problems effectively. Lastly, Yang et al. [35] proposed the Virtual Bee Algorithm to engineering optimizations, demonstrating its effectiveness in comparison to genetic algorithms. Huo et al. [36] introduced a multi-objective artificial bee colony incorporating regulation mechanisms, resulted in improved accuracy and faster execution time. Panniem et al. [37] proposed an adapted artificial bee colony incorporating a firefly algorithm strategy to address issues of gradual convergence and local solution trapping. Li et al. [38] hybridized quantum computing and bee colony optimization, resulting in a quantum-inspired bee colony algorithm that outperformed the classical method. Xin [39] further improved the standard artificial bee colony algorithm by introducing an adaptive Cauchy mutation, which effectively prevented falling to local optima and improved solution quality. Drezner et al. [40] proposed a new parent selection rule in genetic algorithms, which improved results without increasing computing time. This is in line with the findings of Krishnanand et al. [41], who compared the performance of genetic algorithms with other bio-inspired evolutionary optimization techniques and found them to be effective. Gen et al. [42] and Reddy et al. [43] both highlighted the potential of genetic algorithms, with Mitchell emphasizing their simplicity and effectiveness in solving complex problems, and Reddy discussing their application in various fields. These studies collectively underscore the potential of bio-inspired optimization methods in solving a diverse array of complex problems.

5. Methodology

Our proposed approach, based on a hybridization of two metaheuristics, the artificial bee colony algorithm and the genetic algorithm, was developed to treat the problem. Metaheuristics are commonly used to solve this NP-hard problem with high computational complexity.

This work addresses the capacitated vehicle routing problem using a hybrid approach that combines the Genetic Algorithm (GA) and the Artificial Bee Colony (ABC) algorithm. The ABC algorithm is adapted in such a way that the employed and onlooker bee phases utilize GA operators; selection, crossover, and mutation; to explore and improve solutions.

5.1. Initialization

It consists of encoding each food source this type of discrete optimization problems. The algorithm begins by creating *N* initial solutions, which serve as the initial food sources to be explored in the first phase of the HABC (Hybrid Artificial Bee Colony). Each food source in the HABC algorithm is a feasible solution to CVRP, which consists of a list of routes. Each route, containing a sequence of nodes (customers) is assigned to one vehicle. The example in Figure 2 represents the solutions, where 0 represents the depot and the integer numbers represent the client location.

The initial population is created using the following method: a random node is chosen as the route's initial node, and the subsequent requests are added sequentially to the route to ensure satisfaction of the capacity constraint and the total number of vehicles required to obtain a feasible solution.

5.2. Mathematical Formulation

Let:

- $x_{ij} \in \{0,1\}$: binary decision variable indicating if arc *(i, j)* is traversed,
- d_{ij}: distance between nodes *i* and *j*,
- q_i: demand at customer *i*,
- *Q*: vehicle capacity,
- *K*: number of available vehicles,
- u_i: auxiliary variable for sub tour elimination.
- Minimize the total travel cost or distance covered by all vehicles:

$$\text{Minimiser } f(x)=\sum_{i\in N}\sum_{j\in N} x_{ijk} * d_{ijk} \quad (1)$$

- Each customer is visited exactly once by one vehicle:

$$\sum_{i=1}^{N}\sum_{k=1}^{K} x_{ijk} = 1, \quad j = 2, \dots, N \quad (2)$$

- Each customer is departed from exactly once by one vehicle:

$$\sum_{j=1}^{N}\sum_{k=1}^{K} x_{ijk} = 1, \quad i = 2, \dots, N \quad (3)$$

- Each vehicle returns to the depot exactly once:

$$\sum_{i=1}^{N} x_{i0k} = 1, \qquad \forall\ k \in K \quad (4)$$

- Each vehicle departs from the depot exactly once:

$$\sum_{j=1}^{N} x_{0jk} = 1, \qquad \forall\ k \in K \quad (5)$$

- Flow conservation (continuity of the route):

$$\sum_{i=1}^{N} x_{iuk} - \sum_{j=1}^{N} x_{ujk} = 0, \forall\ k \in K, \forall\ u \in N \quad (6)$$

- Load update constraint (to avoid sub-tours):

$$x_{ijk} = 1 \Rightarrow y_{jk} = y_{ik} + q_i\ , \forall k \in K, \forall\ i,j \in N \quad (7)$$

- Load update constraint (to avoid sub-tours):

$$y_{0k} = 0, \qquad \forall k \in K \quad (8)$$

- Vehicle capacity constraint:

$$0 \le y_{jk} \le Q_k \qquad \forall\ k \in K, \forall\ j \in N \quad (9)$$

5.3. Proposed hybrid ABC and GA

The hybrid model modifies the standard ABC algorithm by embedding GA operators into the employed and onlooker bee phases. Each bee manipulates a solution represented as a sequence of customer nodes.

The Artificial Bee Colony approach simulates the intelligent food-search behavior of a honey bee swarm; it is one of the most recently developed swarm-based optimization techniques. It mimics the behavior of real bees in solving an optimization problems [5]-[8] and involves three types of bees: employed bees, onlooker bees, and scouts bees. The employed bees represent the first half of the colony, while the onlooker bees make up the second half.

A bee whose associated food source cannot be improved becomes a scout bee. During the employed and onlooker bee phases, we incorporate GA operators [44], [45] to enhance solution quality. The GA, introduced by John Holland in the 1970s [46] is inspired by the natural process of evolution. It typically involves three main operators: selection, crossover, and mutation [10], [44], [47], which are used to generate a new population that is fitter than the previous one:

- Selection: The food source with the best fitness value is chosen. This selection is based on fitness scores, where better solutions are more likely to be selected.
- Crossover: New food sources (offspring) are produced by exchanging genes between parent solutions. The exchange may involve several genes, and the offspring from a new population.
- Mutation: A modification in the gene sequence of a food source is applied to maintain diversity within the population. It helps avoid local optima by randomly altering the visit order of customer nodes. For example, two nodes from different routes may be swapped.

Once the employed and onlooker phases are complete, a scout bee generates a new solution if an employed bee has failed to improve its solution after a certain number of attempts. This new solution is generated using the same initialization procedure as the original population.

This hybridization combines the global search capabilities of GA with the distributed and adaptive search strategy of ABC, resulting in enhanced performance for solving combinatorial routing problems.

Unlike previous works that merely chain or alternate the use of GA and ABC phases, our proposed HABC introduces a tighter integration where GA's evolutionary operators are deeply embedded into ABC's core search mechanism. This technical innovation allows each bee to not only follow the colony-based decision rules of ABC but also to apply evolutionary pressure during solution updates. Specifically, the crossover and mutation operations are used within the decision cycles of employed and onlooker bees rather than as post-processing or separate phases. This results in a more dynamic and adaptive exploration-exploitation trade-off, which improves convergence speed and reduces the chance of getting trapped in local optima.

The hybrid ABC-GA algorithm proceeds as follows:

1. **The Initial population** is generated using random permutations of customer nodes.
2. **Employed bees** apply GA operators to explore neighboring solutions.
3. **Onlooker bees** refine elite solutions using the same GA operators.
4. **Scout bees** introduce diversity by replacing stagnant or unproductive solutions.
5. The process repeats until a maximum number of generations is met.

Figure 3 illustrates the overall process of this research work. It begins by generating an initial population where each solution contains a sequence of nodes to be visited by the vehicles. These nodes are mapped in a 2D plane, and their coordinates are provided in the text file. The proposed HABC algorithm is then applied to each solution in the population to determine routes that minimize both the total distance traveled and the number of vehicles used.

6. Results and Discussion

The working environment consists of C++ software executed on a personal computer equipped with an Intel Core i5, 2.60 gigahertz, 64-bit processor with 4 gigabytes of RAM, and running Windows 8 OS. To assess the performance of HABC in addressing the Capacitated Vehicle Routing Problem (CVRP), we evaluate it across various instances. These instances include those proposed by Augerat [48], covering a range of nodes from 16 to 100. In addition, we examine a case study investigated by Wang [49] and Pham [50], which involves 8 nodes. Furthermore, we consider another case study presented by Pham [50], featuring 30 nodes. Through this comprehensive analysis, we aim to gain insights into the effectiveness of HABC for the CVRP across different problem sizes and scenarios.

Four parameters are required for the proposed HABC algorithm to efficiently perform on different data sets. To determine the best parameter setting, tests are performed on the number of food sources, the number of iterations, and the limit (number of trials). After several preliminary experiments, the maximal number of food sources (colony size), the maximal number of iterations, the crossover rate, and the maximal limit are provided in table 1.

6.1. Experimentation on the first dataset

The procedure utilized a fleet comprising two vehicles, with each vehicle capable of accommodating up to eight units. Further information regarding the distances between clients and their specific delivery requisites can be found in the references provided [49], [50].

The performance of our proposed algorithm was evaluated by comparing it with the algorithms developed by Wang [49] and Pham [50]. The results of this comparison are summarized in Table 2. In Table 2, the first column represents the total distance obtained by our proposed approach, while the second column indicates our retrieved set of routes. The best-known solution obtained by Wang et al. [49] is presented in column 3, and the solution obtained by Pham et al. [50] is presented in column 4. An analysis of Table 2 reveals that our proposed approach is capable of achieving the same best solutions as those found in the literature.

6.2. Experimentation on the second dataset

To evaluate the performance of the proposed algorithm, it was also applied to another dataset available from [50]. In this particular problem instance, a fleet consisting of five vehicles, each with a capacity of 700 units, was used.

Comparative analysis against DSSA [50] and HABC revealed that our proposed approach yielded superior results. The summarized comparison results are presented in Table 3. In this table, the first column denotes the total distance obtained by our proposed approach, while the second column showcases the corresponding set of routes retrieved. Additionally, the third column displays the solution obtained by Pham et al. [50].

This comparative evaluation not only demonstrates the efficacy of our proposed algorithm but also highlights its competitiveness against existing state-of-the-art approaches.

6.3. Experimentation on the third dataset

To evaluate the performance of the proposed algorithm, we extended its application to another dataset, which is available for download from [48]. The outcomes of this evaluation are visually depicted in Figure 4 and Figure 5, showing the results obtained for the P-n16-k8 and P-n22-k2 datasets, respectively.

In these figures, the graphical representation illustrates the optimal solution achieved by the HABC algorithm. Each point on the graph corresponds to a client, while the edges represent the routes traversed by the vehicles. The node labeled '0' signifies the depot. Each distinctively colored route illustrates the path taken by a vehicle, starting at ending at the designated depot.

The selection of the P-n16-k8 dataset for graphical representation was intentional due to its manageable size, comprising only 16 clients and 8 vehicles. This choice ensures a clear visualization of all the routes, facilitating a comprehensive understanding of the algorithm's performance.

The computational results for the selected instances are presented in Table 4. From left to right, the columns display the dataset name, the minimum number of vehicles used, the optimal total distance obtained by HABC, and the computational time, respectively. For instance, the best-known solution for an instance with 22 nodes and 8 vehicles is 474, consisting of four routes. Each sub-route is bidirectional, as the source data is provided in a symmetric matrix. In certain instances, the proposed HABC approach outperformed results from the literature, which are highlighted in bold in Table 4. Additional comparative results from other algorithms are available in [48].

By comparing Figure 4 and Figure 5, increases with the number of vehicles and clients. The graphical representation also becomes more intricate with larger problem sizes. However, as the problem size grows (both in terms of customers and vehicles), computational time increases significantly, highlighting the computational complexity of solving larger instances optimally.

For smaller instances, such as P-n16-k8 and P-n19-k2, computational times are relatively short, 3 seconds and 33 seconds, respectively. These smaller instances, with fewer customers and vehicles, allow the solver to reach optimal solutions more efficiently. However, as problem size and complexity increase, computational time increases considerably. For example, P-n55-k15 requires 809 seconds, while P-n60-k15 exceeds 1000 seconds.

The number of vehicles also plays a critical role in computational time. Instances with more vehicles generally require longer computation times. For example, comparing P-n50-k7 (7 vehicles, 360 seconds) with P-n50-k10 (10 vehicles, 399 seconds) shows a clear increase. Similarly, P-n55-k7 (535 seconds) and P-n55-k15 (809 seconds) demonstrate how adding vehicles significantly impacts runtime.

However, this relationship is not strictly linear. Factors such as problem-specific constraints, routing complexity, and solution space size also contribute to variations in computational time. For instance, while P-n76-k4 (950 seconds) and P-n76-k5 (978 seconds) show similar computation times despite differing vehicle counts, P-n101-k4 exhibits a significant jump to 1890 seconds, primarily due to the larger dataset size.

It is worth noting that the proposed methods require longer computation times for large problem instances. This increased computation time is justified by the simultaneous generation of routing sequences and the iterative adjustments to customer routes performed during HABC iterations.

To statistically assess whether the improvements brought by the proposed HABC algorithm are significant compared to benchmark solutions, we applied the Wilcoxon signed-rank test on the obtained results. The test yielded a Wilcoxon statistic of 29.0 and a p-value of 0.0015. As the p-value is well below the commonly accepted threshold of 0.05, we can conclude that the performance differences are statistically significant.

7. Limitations

It is important to note that the proposed HABC algorithm tends to require longer computation times as the size of the problem increases. This is mainly due to the complexity of the algorithm, which must perform multiple tasks simultaneously during its execution. First, the algorithm generates optimal routing sequences for each vehicle, ensuring that each customer is served in a way that minimizes the total distance traveled. This task becomes significantly more complex as the number of customers and vehicles increases.

In addition to generating the sequences, the algorithm makes iterative adjustments to the customer routes to refine solutions and improve the overall objective. This iterative process requires evaluating numerous possible configurations, leading to an increased computational load. The hybrid nature of HABC, combining the strengths of the Artificial Bee Colony (ABC) algorithm and the Genetic Algorithm (GA), further amplifies the time complexity, as both algorithms contribute to the exploration and optimization of the search space.

Furthermore, larger problem instances, such as those with more vehicles or customers, introduce an exponentially larger solution space, requiring more time to explore and refine potential solutions. The increase in the number of vehicles and routes adds to the challenge of ensuring the feasibility of each solution while maintaining computational efficiency.

8. Conclusions

The objective of this study is to find the optimal route with the minimum number of vehicles, addressing various vehicle routing with satisfying vehicle capacities. This objective was achieved by hybridizing the ABC with the GA. A case study was presented involving a routing problem for delivering merchandise between 16 and 100 different destinations. The proposed HABC algorithm was implemented and simulated in a C++ program. The simulation results showed that the HABC algorithm effectively solved the routing problem, with the optimal solution obtained within a number of iterations for each instance. Experimental results demonstrate that HABC outperforms the other algorithms in resolving the capacitated vehicle routing problem, offering better computational performance, stronger search optimization capabilities, and greater adaptability and robustness. However, the HABC algorithm has only been applied to the static CVRP problem.

This paper combined two well-studied metaheuristics: the artificial bee colony algorithm and the genetic algorithm, both of which offer promising solutions and open up several future research avenues. Future research could explore other extensions of combinatorial optimization problems in the context of VRPs.

Additional areas for future investigation include incorporating time window constraints to manage specific delivery timeframes and applying the HABC algorithm to dynamic VRP, which involves the fluctuating presence of customers needing service throughout the problem solving process.

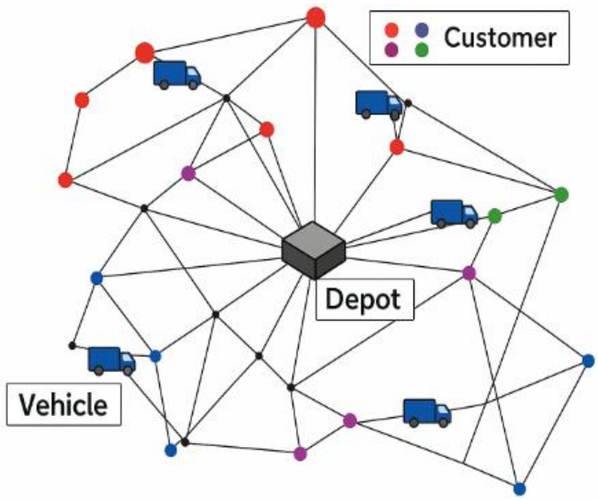

Figure 1. Example of CVRP

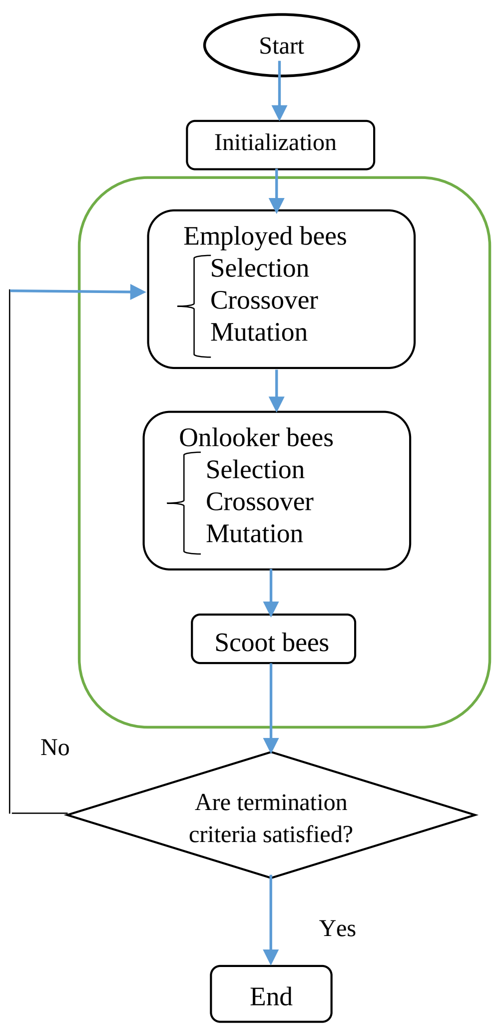

Figure 2. Diagram of HABC

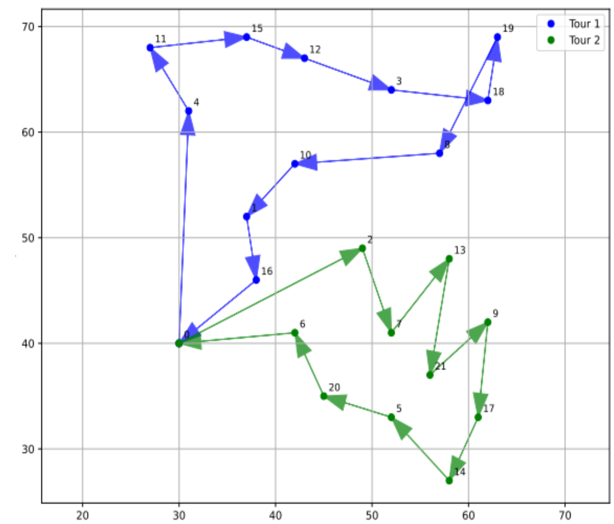

Figure 3. Best routes for the P-n16-k8 dataset

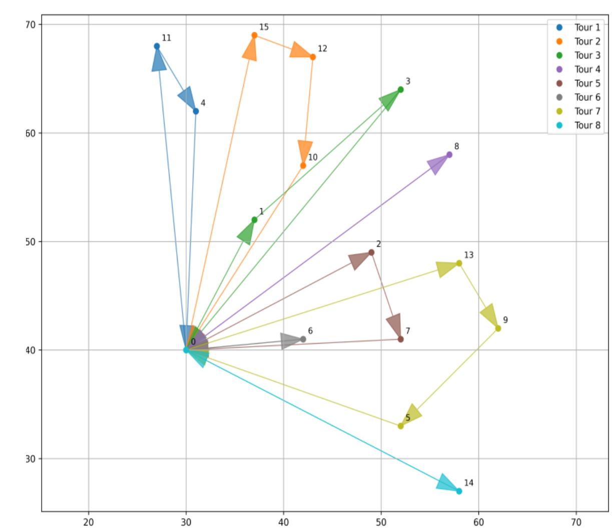

Figure 4. Best routes for the P-n22-k2 dataset

Table 1. Food source solution

Position	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
routes	0	1	2	3	0	8	6	7	4	5	0

Table 2. Parameter values for HABC

Parameters	**Value**
Number Food Source	200
Iteration Crossover rate	50 10
Limit	21

Table 3. Comparative study

Total distance	**Routes**	**Wang et al.**	**Pham et al.**
67.5	0 4 7 6 0	67.5	67.5
	0 2 8 5 3 1 0		

Table 4. Result of two algorithms

Total distance	Routes	Pham et al.
755.91	0 19 17 1 14 3 0	785.87
	0 12 28 5 15 2 25 29 26 0	
	0 24 30 23 8 4 0	
	0 9 20 21 18 10 16 0	
	0 22 7 13 11 27 6 0	

Table 5. Computational results for set P of Augerat

Instance	Vehicles used	Optimal solution	Computational time (s)
P-n16-k8	8	450	3
P-n19-k2	2	220	33
P-n20-k2	2	221	80
P-n21-k2	2	214	86
P-n22-k2	2	225	91
P-n22-k8	**4**	**474**	126
P-n23-k8	8	537	146
P-n40-k5	5	505	309
P-n45-k5	5	**486**	323
P-n50-k7	7	597	360
P-n50-k8	8	669	388
P-n50-k10	10	742	399
P-n51-k10	10	774	517
P-n55-k7	7	618	535
P-n55-k10	10	733	580
P-n55-k15	15	**983**	809
P-n60-k10	10	817	572
P-n60-k15	15	1028	1008
P-n65-k10	10	869	590
P-n70-k10	10	898	901
P-n76-k4	4	749	950
P-n76-k5	5	777	978
P-n101-k4	4	925	1890

Conflict of Interest Statement

The authors declare that there is no conflict of interest in the study.

CRediT Author Statement

Amel Mounia Djebbar: Conceptualization, Methodology, Conducting the experiments, Writing-original draft, Formal analysis.
Amina Kemmar: Supervision, Validation, Writing - review & editing.

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