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Vehicle Routing Problems Based on Harris Hawks Optimization

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Abstract

The vehicle routing problem (VRP) is one of the challenging problems in optimization and can be described as combinatorial optimization and NP-hard problem. Researchers have used many artificial intelligence techniques in order to try to solve this problem. Among these techniques, metaheuristic algorithms that can perform random search are the most promising because they can be used to find the right solution in the shortest possible time. Therefore, in this paper, the Harris hawks optimization (HHO) algorithm was used to attempt to solve the VRP. The algorithm was applied to 10 scenarios and the experimental results revealed that the HHO had a strong ability to check for and find the best route as compared to other metaheuristic algorithms, namely, simulated annealing and artificial bee colony optimization. The comparison was based on three criteria: minimum objective function obtained, minimum number of iterations required and satisfaction of capacity constraints. In all scenarios, the HHO showed clear superiority over the other methods.

Keywords: Vehicle Routing Problem, Harris Hawks Optimization, Metaheuristic, Optimization

1. Introduction

Urban expansion and the growth of cities in particular has led to an increase in factory activity and consequently an increase in various transportation services as companies in a variety of sectors strive to meet the economic and commercial needs as well as the service requirements of the urban population [1]. This trend has generated an increase in logistical research aimed at ensuring that transportation services are both time-efficient and cost-effective in order to improve geographical coverage, speed of service and customer satisfaction [2-4].

One of the most important approaches that has been adopted to try to enhance the efficiency and growth of distribution systems is the vehicle routing problem (VRP), which was first proposed by Dantzig and Ramser in 1959 [5]. The VRP emerged from an existing optimization problem, namely, the traveling salesman problem (TSP) [6] and remains the most structured and researched transport model available. The VRP model attempts to discover how to deliver goods to customers by using a fleet consisting of a predefined number of vehicles. The key goal is to find the minimum-length route that starts and ends in a depot, taking into account a number of variants such as the time window, service time, and vehicle capacity among others [7]. The VRP is a combinatorial optimization and NP-hard problem [8, 9] and several algorithms have been proposed in order to solve it, yet it remains an incredibly important challenge in the field of combinatorial optimization [10]. The only small-scale VRP technology yet discovers the ultimate global solution [11]. The expertise of stream VRP algorithms is divided into exact and heuristics algorithms [12].

Classical heuristics for the VRP can be split into constructive heuristics and improvement heuristics [13]. The origin heuristics forever, progress from a solution to a best one in its neighborhoods [14]. Heuristic methods execute a comparatively limited exploration of the search space and typically require a short computation time to output solutions that have good fitness [15]. Classification heuristics for the VRP include the savings algorithm, route-first cluster-second, cluster-first route-second, and insertion heuristics. Two kinds of improvement algorithms are suitable for the VRP, namely, intra-route heuristics and inter-route heuristics [16].

Metaheuristics are also widely used in optimization problems including the VRP [17-19]. These smart algorithms are suitable for solving hard optimization problems that require a large amount of time because they are able to reach optimal solutions in a fast time [20, 21],

which is largely due to their utilization of random search instead of full search when exploring the search space [22].

Many metaheuristic algorithms have been applied to optimization problems, such as the mine blast algorithm [23], monarch butterfly algorithm [24], and many others [25-29]. The metaheuristic algorithms that have been applied specifically to the VRP include artificial bee colony (ABC)[30], practical swarm optimization(PSO)[31], Ant Colony Optimization (ACO)[32],harmony search [33],genetic algorithm [34] and others[35-42].In line with the literature, this paper uses the Harris hawks optimization (HHO) algorithm to solve the VRP [43], as this algorithm has been shown to have scientific strength in the area of complex optimization problems [44].

The rest of this paper is organized as follows: In Section 2, the related works on VRP are described. Then, in Section 3, the HHO algorithm is discussed in detail. This is followed by a demonstration of the proposed method of using HHO for VRP in Section 4. After that, in Section 5, the experimental results are presented and analyzed. Finally, in Section 6 some conclusions are made and some possible directions for future improvements are suggested.

2. Related Works

In recent times, metaheuristic algorithms have become an important part of the methods that have been developed to solve the VRP, largely because these algorithms have the ability to find optimal solutions due to their robust local and global search capabilities. Several previous studies have used these algorithms to solve the VRP, including Szeto, et al. [45], who presented a heuristic ABC for the capacitated VRP (CVRP). To improve the original heuristic for solving the CVRP, an improved version of the ABC heuristic was developed. Computing tests revealed that the improved heuristic ABC is capable of providing significantly stronger solutions for the CVRP than the original ABC and that it also consumes less computing energy.. In another study, Kantawong and Pravesjit [46]suggested an improved ABC for solving the VRP with time windows (VRPTW). In their work, a fuzzy strategy, scatter search method, and SD-based selection process was incorporated into the ABC. The experimental result showed that the improved algorithm has higher performance than the other algorithm and that it is able to route more vehicles and find a way to ensure that they cover shorter distances as well.

On the other hand, Wang, et al. [47] addressed the periodic VRP with time window and service selection issue by building a heuristic algorithm based on improved ant colony optimization (IACO) and simulated annealing (SA), which they named multi-objective simulate annealing-ant colony optimization (MOSA-ACO). Also using SA, Rabbouch, et al. [48] proposed an empirical-type SA to solve the CVRP. Their approach works incrementally by exploiting the last component of the worst practicable option. The results showed that their method has high search precision, optimal quicker entry, and the ability to classify all optimal rates while increasing the SA algorithm's convergence speed. In another SA-based research study, Ilhan [49] proposed using the population-based SA algorithm to solve the CVRP. Three operators were used to build the process: swap, inclusion and return. In fact, the algorithm used has been evaluated on 63 occasions. The research findings demonstrated that the proposed method has the ability to evaluate the best pathways for 23 instances, along with the presence of the percentage error value and the run time.

Another type of VRP was addressed in [50], where the author suggested an optimization algorithm for a hybrid ant colony and applied it to the multi-depot VRP (MDVRP). The suggested algorithm is based on a mixture of probabilistic techniques that are based on the normal actions of ants when foraging for food as well as on specific techniques that are based on the computational concepts of annealing. The experimental results showed the proposed algorithm is superior to other methods as it is able to produce the smallest mean error. Also, in [51], the authors recommended a way to minimize the MDVRP in terms of both distance traveled and time consumed by using inferential GAs. In their method, the proposed algorithm assigns each depot to its nearest customer and allows each customer to draw one customer at a time before all customers are allocated to drive. In addition, the algorithm uses Dijkstra's shortest path to evaluate each depot's closest customer. The findings showed that the suggested algorithm was calculated from distance and time of travel and thus confirmed its efficacy.

In another recent work, Ruiz, et al. [52] presented a randomized GA that includes a biased key designed to solve open VRP with power and distance constraints. The overall distance traveled by the vehicle is limited, taking into account the limits on ability and vertical speed. The tests demonstrated strong algorithm efficiency in 16 of the 30 cases.

On the other hand, Sethanan and Jamrus [53] suggested the use of both an integer linear programming formulation and a novel hybrid differential evolution algorithm involving a

fuzzy logic controller genetic operator to solve the backhaul and heterogeneous fleet routing problem for multi-trip vehicles . In their work, the objective was to minimize the cumulative cost associated with the distance traveled by using the traditional method of differential evolution and differential evolution with a selected genetic operator and real-settings fuzzy logic controller.

Adopting a different approach, in [54],the authors proposed a hybrid algorithm known as the adaptive cat swarm optimization (ACSO) to solve the VRP. Their method incorporates the benefits of swarm intelligence. Additionally, in order to boost the efficiency of the proposed algorithm, they included strategies to enable the method to leap toward optimum values and thereby promote global convergence. The proposed ACSO was compared with PSO and the original cat swarm optimization (CSO), and it was found that ACSO achieved more accurate results in improving the VRP than other methods.

Meanwhile, in [55],the authors suggested a mathematical model to deal with the issue of the electric VRP (EVRP), taking into account the demands of electrical charging in the operations. To solve this optimization problem, the authors built a dedicated tabu search (TS) algorithm. The results of the improvement the VRP using this approach has obtained more reliable results than other methods. In another hybrid approach, Akbar and Aurachmana [56]also used a TS algorithm, in this case with a GA, in order to refine the CVRP with time windows (CVRPTW). One of the shortcomings of their work is its lack of animation by which to visualize the outcome and thereby encourage future studies. Nevertheless, their findings indicated that the proposed hybrid algorithm not only successfully minimizes the current route, but also estimates the optimal number of homogeneous fleets.

The abovementioned studies are considered to be the most important in terms of the use of metaheuristic algorithms to solve the VRP. Yet, many research studies have used HHO to solve intractable optimization problems. For instance, Gao et al[57] applied HHO with the adaptive generalized Gaussian distribution (AGGD) algorithm for the image denoising issue in order to enhance the obtained results related to Bhandari's mechanism. The results showed that the AGGD algorithm is more effective in terms of accuracy and data processing speed than other models used in this term.

In another HHO-based research study, Jiao et al[58] implemented HHO with chaotic drifts within the vicinity of the most effective and selected agent, and also included an opposition-based exploratory strategy in order to determine the unknown parameters of photovoltaic

model modules. The experimental results showed that the HHO-based identifier provides high-quality solutions for parameter identification cases based on its coherent searching trends.

On the other hand, Jia et al [59] proposed a hybrid HHO and differential evolution (HHO-DE) method for color image segmentation. The obtained results indicated that the proposed approach represents a promising technique for addressing multilevel thresholds in color image segmentation. Also in the image segmentation field, Lang et al [60] implemented a novel satellite image segmentation mechanism consisting of the HHO algorithm and a mutation mechanism, which the authors named the DHHO/M mechanism. The results showed that the DHHO/M mechanism is highly efficient as compared to other existing mechanisms according to the fitness function evaluation, image segmentation effect and statistical tests.

Meanwhile, Moayedi et al [61] used the HHO algorithm in a landslide susceptibility analysis method for implementation in Western Iran. The authors found that the HHO performs effectively in minimizing the learning error of the artificial neural network algorithm. They concluded that, when the created landslide susceptibility maps achieve an acceptable level of accuracy, it is likely that they will be used in decision making and risk management in the future.

In a different research direction, Yıldız et al [62] implemented the HHO algorithm, grasshopper optimization algorithm (GOA) and multi-verse optimization (MVO) in order to optimize the processing parameters for manufacturing procedures and grinding operations. The results of their analysis indicated that the HHO, GOA and MVO algorithms represent effective optimization mechanisms for acquiring optimal manufacturing variables for different manufacturing operations. In a related work, Yıldız et al [63] applied the Nelder–Mead local search algorithm with the HHO, which the authors named H-HHONM, in order to optimize the procedure parameters for milling operations. The authors demonstrated that the H-HHONM method is efficient at optimizing manufacturing and design issues.

The final work worthy of mention here is that by Zobaa et al [64], who applied HHO to obtain an optimal planning solution for a resonance-free C-type harmonic filter in order to reduce the harmonic overloading level of frequency-dependent items within a non-sinusoidal distribution system. In comparison with existing optimizers, the proposed method that

involved the use HHO led to high efficiency when the lowest power loss with the harmonic overloading level related to the frequency-dependent components.

Based on the foregoing review of related works, it can be seen that several different metaheuristic algorithms have been used to solve the VRP and its variants. The results obtained by previous research studies showed that these smart algorithms can find the best routes for vehicles to reach customers in the least possible time. The success of these algorithms is due to the precision of their random search mechanism, and to the balance they achieve between the local and global search processes. The review also revealed that researchers have used the HHO algorithm to solve a range of complex optimization problems. It therefore seemed logical to investigate whether HHO would be able to find optimal solutions for the VRP.

3. Harris Hawks Optimization

The HHO algorithm is a new swarm intelligence optimization algorithm that was proposed by Heidari et al in 2019 [43]. The algorithm has been shown to perform efficiently in the optimization domain relative to other metaheuristic algorithms. Moreover, the algorithm can be extended to solve multiple types of optimization problems successfully, exhibiting a good level of performance [65]. Centered on the effects of such an algorithm in problems of intricacy optimization, the study uses it to increase the efficiency related to the VRP [43].

The basic notion behind the improved algorithm is derived from how Harris hawks hunt for food under desert conditions which are characterized by a scarcity of food [66]. To find their prey, Harris hawks engage in a variety of complex processes of mutual hunting and coordination to find, encircle, flush out and ultimately strike a possible target or prey. The HHO algorithm mimics the behavior of these hawks that monitor and catch their prey by means of a “surprise pounce”, which is also known as the “seven kills” strategy [43]. In this strategy, many hawks collaboratively target a single prey, such as a rabbit that is out in the open rather than hiding under cover of vegetation for example, by using different techniques and they ultimately converge on this prey [61].

The attack can be terminated promptly by catching the shocked target in just a few seconds. However, depending on the prey’s escape capability and habits, the hawks may need to undertake several, short-length, swift dives that are likely to be in the vicinity of the prey for several minutes [44] before they are successful in executing the seven kills strategy. Harris

hawks display a variety of types of chasing, which depends not only on the prey's escape habits, but also on a diverse range of environmental circumstances. For instance, in a swooping chase scenario, the most successful hawk (leader) swoops at the prey to capture it, but it can miss the prey (i.e., not find the target solution) because in essence the search and attack is carried out by a single member of the group. By increasing its vulnerability, Harris hawks proceed to locate an exhausted rabbit. In the end, when only one hawk, usually the most seasoned and strongest, can easily catch the exhausted rabbit and share it with the extant members, it cannot run away from the team besiege [67].

The HHO algorithm consists of three phases: 1) discovery or exploration (global search), 2) transformation from exploration to exploitation, and 3) exploitation (local search) [66]. For the intention of finding and investigating all aspects relevant to these propositions, the discovery phase reflects the change to many locations and a new venue. In addition, this phase illustrates a new technique for studying. The transformation from discovery to exploitation phase is regarded as crucial to the success of metaheuristic algorithms. In HHO, in order to transform the specified phases, the escape energy of the rabbit prey is used. The utilization process, on the other hand, reflects the installation and use of such sites and enables the available resources to be completely implemented [68].

3.1. Exploration phase

In this algorithm, the Harris hawks perch in certain positions frequently and wait to spot a target based on two techniques that are formulated in Eq. 1:

$$X(t + 1) = \begin{cases} X_{rand}(t) - r_1 |X_{rand}(t) - 2r_2 X(t)| & q \geq 0.5 \\ (X_{rabbit}(t) - X_m(t)) - r_3 (LB + r_4 (UB - LB)) & q < 0.5 \end{cases} \quad (1)$$

where $X(t + 1)$ is the hawks' location vector in the next iteration t , $X_{rabbit}(t)$ is the rabbit's position, $X(t)$ is the hawks' current location vector, r_1 , r_2 , r_3 , r_4 , and q are random numbers within (0,1) that are modified in each iteration, LB and UB represent the upper and lower variable borders, $X_{rand}(t)$ is a hawk randomly selected from the current population, and X_m is the mean variable position. The average position of the hawks is reached by using Eq. 2:

$$X_m(t) = \frac{1}{N} \sum_{i=1}^N X_i(t) \quad (2)$$

where the position of each hawk in iteration t is indicated by $X_i(t)$ and N refers to the total number of hawks.

3.2. Transition from exploration to exploitation

In order to represent this step, the rabbit's energy is formulated as in Eq. 3:

$$E = 2E_0 \left(1 - \frac{t}{T} \right) \quad (3)$$

where E denotes the fleeing energy of the rabbit, T is the cumulative number of iterations, and E_0 is the rabbit's initial energy state.

3.3. Exploitation phase

In the final exploitation phase, the hawks employ four different types of besiege technique to capture their prey.

3.3.1. Soft besiege

The following rules in Eqs. 4 and 5 describe the soft besiege behavior of the Harris hawks:

$$X(t+1) = \Delta X(t) - E |JX_{rabbit}(t) - X(t)| \quad (4)$$

$$\Delta X(t) = X_{rabbit}(t) - X(t) \quad (5)$$

where $x(t)$ is the variance between the rabbit's place vector and the specific position in iteration t during the escape process, r_5 is a random number within (0,1), and $J = 2(1 - r_5)$ defines the rabbit's random leap ability. To mimic the nature of the rabbit's movements, the J value varies arbitrarily with each iteration.

3.3.2. Hard besiege

For a hard or intense besiege, the existing positions of the hawks are adjusted by Eq. 6:

$$X(t+1) = X_{rabbit}(t) - E |\Delta X(t)| \quad (6)$$

3.3.3. Soft besiege with progressive rapid dives

When a soft besiege is accompanied by rapid dives, it is assumed that the hawks decide on adopting this technique based on the following rule in Eq. 7:

$$Y = X_{rabbit}(t) - E |JX_{rabbit}(t) - X(t)| \quad (7)$$

It is also assumed that they use the following rule in Eq. 8 to dive at the prey based on Lévy flight-based patterns:

$$Z = Y + S \times LF(D) \quad (8)$$

where D is the issue aspect, S is a random vector of size 1 multiplied by D, and LF is the Lévy flight function that is determined using Eq. (9):

$$LF(x) = 0.01 \times \frac{\mu \times \sigma}{|v|^{\frac{1}{\beta}}}, \sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \quad (9)$$

where u and v within (0,1) are random values, and β is the default constant that is fixed to 1.5.

The final technique that is used to upgrade the positions of the hawks that are in the process of undertaking a soft besiege with dives can then be carried out by Eq. (10):

$$X(t+1) = \begin{cases} Y & \text{if } F(Y) < F(X(t)) \\ Z & \text{if } F(Z) < F(X(t)) \end{cases} \quad (10)$$

where Y and Z are obtained by using Eqs. 7 and 8.

3.3.4. Hard besiege with progressive rapid dives

The final technique involves the combination of a hard besiege and rapid dives, as formulated in Eq. 11:

$$X(t+1) = \begin{cases} Y & \text{if } F(Y) < F(X(t)) \\ Z & \text{if } F(Z) < F(X(t)) \end{cases} \quad (11)$$

where Y and Z are obtained by using the new rules in Eqs. 12 and 13:

$$Y = X_{rabbit}(t) - E |JX_{rabbit}(t) - X(t)| \quad (12)$$

$$Z = Y + S \times LF(D) \quad (13)$$

where $X_m(t)$ is obtained using Eq. 2.

All of these steps of HHO are described in the following algorithm pseudocode [43] :

Pseudocode of HHO Algorithm

- 1- Inputs:** Size N of the population and overall number of iterations (N).
- 2- Outputs:** The positioning of rabbits as well as their fitness value.
- 3- Initialize** Random population X_i , $i = 1, 2, \dots, n$.
- 4- While** stopping position is not satisfied **do**:
- 5- Determine** the fitness values of hawks
- 6- Set** X_{rabbit} as the location of rabbit with ‘the best location’.
- 7- for** (every hawk (X_i)) **do**
- 8- Modify** the initial energy E_0 as well as jump strength J
- 9- $E_0 = 2 \times \text{rand}() - 1$, $J = 2(1 - \text{rand}())$**
- 10- Modify** the E by Eq. 3
- 11- if** ($|E| \geq 1$) **then** go to Exploration phase
- 12- Modify** the location vector by Eq. 1
- 13- if** ($|E| < 1$) **then** go to Exploitation phase
- 14- if** ($r \geq 0.5$ and $|E| \geq 0.5$) **then** go to Soft besiege
- 15- Modify** the location vector by Eq. 4
- 16- else if** ($r \geq 0.5$ and $|E| < 0.5$) **then** go to Hard besiege
- 17- Modify** the location vector by Eq. 6
- 18- else if** ($r < 0.5$ and $|E| \geq 0.5$) **then** go to Soft besiege
- 19- With** quick radical dives
- 20- Modify** the location vector using Eq. 10
- 21- else if** ($r < 0.5$ and $|E| < 0.5$) **then** go to Hard besiege
- 22- With** quick radical dives
- 23- Modify** the location vector by Eq. 11
- 24- Return** X_{rabbit}

4. Proposed Method: HHO for VRP

In this paper, we suggest using HHO to construct a routing strategy by focusing on minimizing the number of vehicles in two steps:

4.1 Stage 1

The HHO global search functionality is used in the first step, with the HHO fitness function defined as:

$$f(\sigma) = (|\sigma|, \sum_{i=1}^{|\sigma|} c(\sigma_i)) \quad (14)$$

where $|\sigma|$ is the number of routes in the σ routing strategy and $c(\sigma_i)$ is the travel expense of the σ_i route $\in \sigma$.

In the first iteration, the rabbit randomly chooses a direction of travel. A fitness function is calculated when it hits its destination (e.g., the transport distance) and the artificial pheromones are evaluated and identified by the network. These artificial pheromones affect the next hawk's preference. In the subsequent iterations, the rabbits appear to take the shorter direction. In addition, the chance of better pathways being chosen can be improved by artificial pheromones.

The decrease in the number of vehicles is typically the complication, instead of the primary feature of the searching process, of reducing transport costs. In VRP-SPDTW, because reducing the number of vehicles and travel costs are both important targets, we concentrate on one of them in each process.

4.2 Stage 2

In the second stage, the local search of HHO minimizes the travel cost by using the routing plans that were generated in Stage 1 as the initial solution. The search in this stage continues until a certain stopping condition is met.

Figure 1 shows the mechanism of the suggested method.

Figure 1: Applying HHO in VRP

There are three conditions that must be taken into account when solving the routing problem: 1) the vehicle starts from the warehouse and returns to it, 2) the vehicle visits one customer only in one journey and then returns to the place of departure i.e., the warehouse) before going to another customer and 3) the customer may not request a delivery from more than one vehicle.

Furthermore, each vehicle must not exceed a specific load (capacity), which is defined as follows:

$$\text{Capacity} = \text{ceil} (N/K) \quad (15)$$

where N is the number of nodes (customers) and K is the number of vehicles.

As for addressing the issue of time complexity, the HHO's computational complexity depends primarily on three processes: initialization, fitness assessment, and hawk update [43]. The time complexity of the initialization process is $O(N)$ for N hawks. While $O(T \times N) + 25 O(T \times N \times D)$ is the computational complexity of the updating process, which consists of looking for the best location and updating all the hawks' location vectors, where T is the maximum number of iterations and D is the dimension of unique problems. Consequently, $O(N \times (T + TD + 1))$ is the computational complexity of HHO.

5. Experimental Results

The proposed method was performed on a Notebook that had a Windows 10 operating system, an Intel Core i7 processor and 16 GB of RAM. Since the input variables play an essential role in the consistency of the solutions, a few preliminary studies were conducted to establish the parameter settings. The final set of parameters is specified in Table 1.

Table 1: Parameter Settings

Parameter	Value
T: maximum number of iterations	200
N: population size	100
Lower bound (LB)	0
Upper bound (UB)	1
Number of hawks	10
Number of iterations	30
Model.etu (learning rote)	0.0001

5.1 Application of HHO to 10 VRP Scenarios

First, the HHO algorithm was applied to solve the VRP using 10 scenarios, where each scenario consisted of different numbers of customers and vehicles. In the first scenario, there were eight customers and three vehicles. These numbers were increased in each subsequent scenario to 70 customers and eight vehicles in the last scenario. This was done to make the problem more complex in order to measure the efficiency of the proposed approach using HHO in reaching the optimal solution for different sized problems. To assess the performance of HHO in each scenario, three criteria were calculated: 1) the minimum objective function obtained, 2) the minimum number of iterations required, and 3) the satisfaction of capacity constraints as explained in Section 4.2. Table 2 shows the results obtained by HHO for the 10 scenarios.

Table 2: Results Obtained by HHO for VRP

Simulation number	Minimum objective function obtained	Minimum number of iterations required	Satisfaction of capacity constraints
Sim. 1 8 customers 3 vehicles	220.1634	13	Yes
Sim. 2 10 customers 3 vehicles	269.8302	28	Yes
Sim. 3 14 customers 4 vehicles	219.2101	51	Yes
Sim. 4 20 customers 4 vehicles	297.457	63	Yes
Sim. 5 25 customers 5 vehicles	251.976	172	Yes
Sim. 6 30 customers 5 vehicles	316.1595	193	Yes
Sim. 7 40 customers 6 vehicles	319.0379	157	Yes
Sim. 8 50 customers 7 vehicles	298.1563	194	Yes
Sim. 9 60 customers 7 vehicles	401.5839	156	Yes
Sim. 10 70 customers 8 vehicles	423.0535	186	Yes

It can be seen from Table 2 that, in all 10 scenarios, HHO succeeded in reaching the optimum solution with a relatively low number of iterations. In addition, HHO was able to satisfy the capacity constraints in all scenarios.

Figure 2 depicts the routes taken by the vehicles in order to reach the customers according to the conditions of the VRP for each scenario. In the figure, the route of each vehicle is depicted using a different color and is the route used to reach each customer at the lowest possible cost.

Figure 2: VRP route maps for each simulation by HHO

5.2 Comparison of HHO against SA and ABC

In order to evaluate the efficacy of the proposed method, the outcomes of the proposed method were compared with those of two methods in the literature, namely, SA [48] and ABC [45]. The comparison was made by using the same parameter settings and criteria outlined above. Table 3 shows the outcomes of all three methods.

Table 3: Comparison of HHO, SA and ABC for VRP

Simulation number	Method	Minimum objective function obtained	Minimum number of iterations required	Satisfaction of capacity constraints
Sim. 1 8 customers 3 vehicles	HHO	220.1634	13	Yes
	SA	220.1634	51	Yes
	ABC	220.1634	61	Yes
Sim. 2 10 customers 3 vehicles	HHO	269.8302	28	Yes
	SA	293.9009	105	Yes
	ABC	284.9794	65	Yes
Sim. 3 14 customers 4 vehicles	HHO	219.2101	51	Yes
	SA	278.3779	230	Yes
	ABC	276.2006	144	Yes
Sim. 4 20 customers 4 vehicles	HHO	297.457	63	Yes
	SA	385.7173	264	Yes
	ABC	334.7739	231	Yes
Sim. 5 25 customers 5 vehicles	HHO	251.976	172	Yes
	SA	376.6583	248	Yes
	ABC	330.3308	224	Yes
Sim. 6 30 customers 5 vehicles	HHO	316.1595	193	Yes
	SA	419.6352	282	Yes
	ABC	354.6163	206	Yes
Sim. 7 40 customers 6 vehicles	HHO	319.0379	157	Yes
	SA	549.2129	294	Yes
	ABC	375.9213	280	Yes
Sim. 8 50 customers 7 vehicles	HHO	298.1563	194	Yes
	SA	626.9496	298	Yes
	ABC	377.2894	292	Yes
Sim. 9 60 customers 7 vehicles	HHO	401.5839	156	Yes
	SA	712.1566	300	Yes
	ABC	416.0673	250	Yes
Sim. 10 70 customers 8 vehicles	HHO	423.0535	186	Yes
	SA	694.4901	300	Yes
	ABC	442.3711	300	Yes

As can be seen from Table 3, in sim.1 with eight customers and three vehicles, all three methods obtained the same minimum objective function of 220.1634 and satisfied the capacity constraints. However, HHO did so more quickly in just 13 iterations. However, in sim. 2 with 10 customers and three cars, SA performed better than HHO and ABC with an objective function of 269.8302. However, again the least number of iterations was achieved by HHO with 28 iterations. All three methods met the capacity constraints of sim.2.

On the other hand, in sim.3 with 14 customers and four cars, HHO outperformed the other algorithms in terms of both the minimum objective function with 219.2101 and the fastest convergence with 51 iterations. Again all algorithms satisfied the capacity constraints. Similarly, in sim.4 with 20 customers and four vehicles, HHO outperformed the other algorithms in terms of objective function and number of iterations of 297.457 and 63, respectively. Likewise, in sim.5 and sim.6, HHO performed better than the other two methods achieving an objective function of 251.976 and 172 iterations and 316.1595 and 193, respectively

Furthermore, HHO was able to achieve the lowest objective function and number of iterations in sim.7, sim.8, sim.9 and sim.10. In sim.7, with 40 customers and six cars, it achieved an objective function of 319.0379 in 157 iterations. In sim.8 with 50 customers and seven vehicles, it had an objective function of 298.1563 and convergence speed of 194 iterations. In sim.9 with 60 customers and seven vehicles, its objective function was 401.5839 and its number of iterations was 156.

Importantly, in sim.10 that had the highest level of complexity with 70 customers and eight vehicles, the lowest objective function was also achieved by HHO with 423.0535. The proposed method also performed the best in terms of convergence speed with 186 iterations.

In sum, in all ten scenarios, all three methods, HHO, SA and ABC, were able to satisfy the capacity constraints. However, HHO was clearly superior to the other two methods in terms of the minimum objective function obtained and the minimum number of iterations required. This indicates that HHO has the ability to achieve a balance between local and global search to reach more accurate solutions in a fast time. Figure 3 provides more details on the number of iterations required in each simulation to reach the optimal solution compared to the other two methods.

Simulation 1: 10 Costumers and 3 Vehicles (10x3)

Simulation 2: 10 Costumers and 3 Vehicles (10x3)

Simulation 3: 10 Costumers and 3 Vehicles (10x3)

Simulation 4: 10 Costumers and 3 Vehicles (10x3)

Simulation 5: 10 Costumers and 3 Vehicles (10x3)

Simulation 6: 10 Costumers and 3 Vehicles (10x3)

Simulation 7: 10 Costumers and 3 Vehicles (10x3)

Simulation 8: 10 Costumers and 3 Vehicles (10x3)

Simulation 9: 10 Costumers and 3 Vehicles (10x3)

Simulation 10: 10 Costumers and 3 Vehicles (10x3)

Figure 3: Convergence speed of all methods

From Figure 3, the strength of HHO in every simulation is readily apparent. The use of HHO is advantageous whether the size of the problem is minimal, moderate or large, as it is able to find an optimal solution in the least number of iterations as compared to the other compared methods. Harris hawk optimization is not only able to find an optimal solution, it can do so quickly. This is due to its architecture, which achieves a better balance between exploration and exploitation, and it can transition smoothly between these two types of search. The number of iterations, i.e., convergence speed, is an important factor in solving complex optimization problems such as the VRP in a timely and cost-effective manner. Hence these results show that HHO has great potential for solving the VRP.

6. Conclusion

The VRP is an important real-world problem and is therefore the focus of much research. In this paper, we proposed using a different metaheuristic, namely, HHO, to solve the VRP because of the reported properties of this algorithm. The performance of HHO was assessed according to three criteria: the minimum objective function obtained, the minimum number of iterations required, and the satisfaction of capacity constraints. Compared with two well-known methods, namely, SA and ABC, the results showed that HHO was clearly superior in terms of both the minimum objective function obtained and the minimum number of iterations required. This is likely due to the advanced exploitative capabilities of HHO as well as its ability to achieve better integration between the local and global search processes. In the future, to achieve better results, HHO could be employed in a hybrid model with another metaheuristic algorithm, or its global search mechanism could be modified through the use of several methods such as a crossover operator.

Declarations

• Ethics approval and consent to participate

We confirm that any aspect of the work covered in this manuscript that has involved human patients has been conducted with the ethical approval of all relevant bodies and that such approvals are acknowledged within the manuscript.

• Consent for publication

We give my consent for the publication of identifiable details, which can include photograph(s) and/or videos and/or case history and/or details within the text (“Material”) to be published in the above Journal and Article. I confirm that I have seen and been given the opportunity to read both the Material and the Article to be published by Journal of big data.

• Availability of data and materials

The data that support the findings of this study are available on request.

• Competing interests

The author(s) declare(s) that they have no competing interests

• Funding

No funding was received for this work.

• Authors' contributions

We attest that all authors contributed significantly to the creation of this manuscript, each having fulfilled criteria. We confirm that the manuscript has been read and approved by all named authors. We confirm that the order of authors listed in the manuscript has been approved by all

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Conflict of Interest

We wish to confirm that there are no known conflicts of interest associated with this publication

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