The ambulance routing problem is one of the capacitated ambulance routing problem forms. It deals with injuries and their requests for saving. Therefore, the main aim of the ambulance routing problem is to determine the minimum (i.e., optimum) required distances of between:

1) accident places and the ambulance station;

2) the location of the nearest hospital and the accident places.

Although of the efforts proposed in the literature, determining the optimum route is crucial. Therefore, this article seeks to tackle ambulance vehicle routing in smart cities using Harris Hawks Optimization (HHO) algorithm. It attempts to take the victims as quickly as possible and confidently. Several engineering optimization problems confirm that HHO outperforms many well-known Swarm intelligence approaches. In our system, let's use the node approach to produce a city map. Initially, the control station receives accident site information and sends it to the hospital and the ambulance. The HHO vehicle routing algorithm receives data from the driver; the data includes the location of the accident and the node position of the ambulance vehicle. Then, the driver's shortest route to the accident scene by the HHO. The locations of the accident and hospital are updated by the driver once the car reaches the accident site. The fastest route (which results in the least travel time) to the hospital is then determined. The HHO can provide offline information for a potential combination of the coordinates of destination and source. Extensive simulation experiments demonstrated that the HHO can provide optimal solutions. Furthermore, performance evaluation experiments demonstrated the superiority of the HHO algorithm over its counterparts (SAODV, TVR, and TBM methods). Furthermore, for ten malicious nodes, the PDF of the algorithm was 0.91, which is higher than the counterparts

Keywords: ambulance vehicle routing, Harris Hawks optimization method, smart city

UDC 621
DOI: 10.15587/1729-4061.2023.278002

HARRIS HAWKS OPTIMIZATION FOR AMBULANCE VEHICLE ROUTING IN SMART CITIES

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Received date 15.02.2023
Accepted date 20.04.2023
Published date 28.04.2023

How to Cite: *Hussein, T. D. H., Frikha, M., Rahebi, J. (2023). Harris Hawks optimization for ambulance vehicle routing in smart cities. Eastern-European Journal of Enterprise Technologies, 2 (3 (122)), 74–81. doi: https://doi.org/10.15587/1729-4061.2023.278002*

1. Introduction

Accidents and disasters can happen naturally or as a result of human actions. On a bigger scale, these catastrophes or accidents may impact both existing infrastructures and people. Due to the difficulty of carrying out efficient logistical operations under these conditions, timely delivery of efficient medical help results in additional losses. Therefore, after a tragedy or accident, rescue and assistance operations must be well planned and carried out [1].

People who have been hurt in an emergency need to be taken to hospitals first. To carry out our mission successfully, the following important points should be considered:

1) the position, number, and capability of ambulances;

2) the number and location of injured persons.

After gathering these details, an emergency schedule must be created to transport incidents to hospitals quickly [2].

Managing and interconnecting heterogeneous devices requires the use of application programs. Consequently, these devices generate a massive quantity of data (big data) [3]. Smart cities utilize distributed computing systems (e.g., cloud computing) to process data. These systems are utilized for real-time analysis of large data sets. Nowadays, big data has been processed using edge computing. Sensor layer capabilities and generating objects are used in the calculations and processing, namely fog computing [4]. Fog computing with a cloud-computing layer can provide smart cities with a high capacity to process large data sets. Smart cities face significant data security challenges despite the importance of managing large data.

As mentioned previously, smart cities manage a substantial quantity of data exchange. For the protection of information confidentiality, data transmission must be protected. The security of medical data (including health-related data) is regarded as one of the most important issues in smart cities. It is crucial to protect the privacy of health-related data transmission over the network and its infrastructure. If the data is intercepted during transmission, sensitive information may be revealed. Accordingly, there is a possibility of losing data conditionality and manipulated data during medical data transmission.

In some cases, manipulation of medical data in smart cities may result in treatment disruptions or even patient deaths. Therefore, in smart cities, medical data encryption is an absolute necessity. The transmission of patient records on the blockchain and the Internet of Things are treatment techniques for other medical facilities [5–7]. Humans play a significant influence in natural disasters and emergencies. These accidents or disasters can have a greater impact on individuals and infrastructures. Effective logistical operations are challenging to execute in such circumstances. Accordingly, medical assistance is not allowed, sometimes resulting in additional losses. Therefore, after disasters or accidents, rescue operations and aid must be managed effectively [1].

The abovementioned problem is known as Capacitated Ambulance Routing Problem (CARP). CARP is one ambulance routing problem (ARP) type, where ARP contains the victims' requests. The main goal is to reduce the ambulance's path as far as possible to take the victims to hospitals. It depends on the emergency that occurred from the location of the ambulance station to the accident place, then to the hospital [8]. Victims are placed into the ambulance from the accident scene and delivered to the hospital. If there is insufficient time to transport all the victims, the vehicle will return to its local station. The answers put out by CARP include precise, heuristic, and meta-heuristic methods. Some academics are putting forward strategies for locating the precise answer. However, due to the CARP's status as an NP-hard non-deterministic polynomial problem, these approaches might be impractical in more complicated accident scenarios. Thus, to effectively tackle CARP associated with the optimum route to the accident site, heuristic and meta-heuristic algorithms are commonly applied. In general, Genetic Algorithm, Ant Colony, Particle Swarm Optimization, Simulated Annealing, etc., were used to solve CARP. For these optimization problems, it is not thought that the different meta-heuristics solution characteristics differ noticeably. The HHO algorithm is the one choosing to employ in this paper because of its established methodology and reliability.

Therefore, nowadays, management systems are a significant concern in ambulance applications. From what we have seen, ambulance vehicle routing is crucial for the health and processing of smart cities.

2. Literature review and problem statements

For ambulance routing, the authors in [1] devised the shortest path algorithm from the accident scene to the hospital. The shortest path between a collection of node locations has been determined using Dijkstra's algorithm. However, because it is a queue-based approach, there may be a delay caused by GSM communications. Effective communication metrologies were achieved in [2], employing communication between an ambulance and a traffic light controller. For adjusting the traffic light signal, this system also uses vehicle-to-infrastructure communication technology. This method involves sending the position of the vehicle and path information to the core network via a brief message waved from the vehicle. Based on the ambulance location, the traffic signal is controlled by the core network. Other cars on the crossing road, on the other hand, only receive a 2.48 percent rise in AAWT. The shortest accident scene to the hospital route in [8] has been determined using a star algorithm. Then, the information is passed to the system that controls the ambulance path. Video image processing was used in [9] to effectively manage traffic light signals, enabling emergency vehicles like ambulances and fire engines, among others. It prioritizes emergency cars regardless of traffic density. This technology uses image processing to analyze the amount of traffic on the road, and the system also picks up the emergency car's RFID signal. Traffic congestion is reduced, and traffic lights are controlled based on this information. For emergency routing application, traffic congestion control-based RFID has been proposed by the authors [10]. Information from every car is read by the RFID system through a roadside capturing unit. Then, the information is sent by the system to the traffic main control unit. In order to safely pass an emergency vehicle crossing the road, the traffic signal will be adjusted by the main traffic control unit.

For emergency vehicle navigation, the authors in [11] suggested a tiny version of the intelligent traffic light system. The system comprises two units mounted in the central control unit and the emergency vehicle. In the emergency vehicle, any emergency case is transferred to the main control unit. After that, the traffic light is controlled to let the emergency vehicle go in the appropriate direction. Expensive requirements are determined by the hardware and software utilized in this type of system. A smart traffic signal control system in smart city applications, was demonstrated in [12]. The modules employed in this system consisted of message broadcasting, roadside unit control, emergency vehicle signal preemption, eco-driving support, public transportation signal priority, and Adaptive traffic signal control. This strategy involves sharing the emergency vehicle's location and heading with other vehicles, which helps to manage traffic around the intersection point and make emergency vehicle room. The time it takes for an emergency vehicle's alert message to reach a non-emergency vehicle is longer than essential. For emergency vehicle routing at neighboring traffic signals, [13] utilized the Li-Fi protocol. The Li-Fi model is fixed with a fixed modulated frequency for every traffic light management system, non-emergency and emergency. When an emergency vehicle is hit by oncoming traffic, the Li-Fi protocol will inform the local traffic light control system to alter the traffic signal.

Using IoT, the authors in [14] proposed an emergency vehicle clearance control. Initially, the system consists of vehicle RFID control, traffic signal RFID control, and the main control server. The vehicle position is transmitted to the main control server. After that, according to traffic, the path of the emergency vehicle is sent by the main control server. When an intersection is nearby, a vehicle RFID control system is employed to alter the traffic light. Intense sunlight and other light sources, such as normal light bulbs, may also interrupt communication. The authors in [15] proposed a smart traffic light system via the MQTT protocol, Google Maps, an Android app, and micro-controlled traffic lights. Google Maps is utilized (by ambulance drivers) to obtain the optimum path to the hospital and the time needed to arrive for every traffic signal. After that, the MQTT protocol is used to send these details to the primary traffic control center. Accordingly, based on the proximity of the vehicle to the traffic signal, the primary traffic control center changes the traffic signal. Increasing the number of repeats by 100 leads to an increase of 7.5 km in the overall distance between the locations.

IoT concept based on traffic light control was created in [16]. This technique uses a GPS and an application server to manage traffic signals and allow emergency vehicles to pass. In the emergency vehicle, the Android application and GPS determine location services and relay the vehicle's location to a server, which then uses that information to manage the traffic light signal. The addition of blue traffic signals may generate misunderstanding. The authors in [17] developed a fuzzy logic-based traffic control system for vehicle clearance. This technology sends the traffic management system the emergency vehicle's level of alertness (TMS). TMS retrieves a road map, information about the amount of traffic on the road, and the average speed of the appropriate path based on the level of emergency. Next, the details are reached by fuzzy logic control. The Fuzzy logic control uses the information to calculate the TMS's congestion level and vehicle. Accordingly, TMS will generate the plan and route of the emergency response, which may then send to the vehicle for fast clearance to the destination. For the routing problem, a genetic algorithm was used in [18]. The genetic algorithm was utilized to construct the shortest way and a new, workable path for the emergency vehicle according to the vehicle's current location, traffic statistics, origin, and destination. The size of the map is a crucial variable in deciding route length.

An updated evolutionary algorithm was used in [19] to solve the problem of emergency vehicle routing. Graph theory was used to build the mathematical model of the route node, and the evolutionary algorithm was used to solve it using the emergency vehicle's origin and destination information. To address the ambulance routing problem, the authors in [20] used mixed integer programming in their design. In the beginning, the proposal determines the victim's information, the number of vehicles nearby the accident, and the location of the hospital. These details are then used to determine the ambulance's optimum path. The number of nearby vehicles compared to the number of casualties remains a point of concern. For the rescue vehicle's navigation, the authors in [21] utilized distributed ant colony optimization in their system. The optimization method can determine the best route so the ambulance can quickly get to the accident site. More mechanisms must be introduced to the infrastructure to regulate system convergence and lead it to the optimum route for quality.

The authors in [22] used Google map distance matrix API to schedule the emergency vehicle routing. Vehicle routing is determined by mixed integer programming according to the incident location, Google map routes, and vehicle tracking. The essential issue is that a one-minute delay in reaction time is unacceptable. Particle swarm optimization and the Petal algorithm were used in [23]. A vehicle routing challenge with a pickup and delivery idea was used to pose the issue. A multi-objective model-based method for ambulance routing was created in Two ambulances are stationed at temporary emergency stations. Discovering the best ambulance route is critical [24]. Therefore, the proposal can identify the best route schedule for the ambulance using the accident site and victim injury level as inputs.

Clustering-based ambulance routing strategies were established in [25]. The method calculated the shortest distance between the patient's location and the hospital using the algorithms: Density Based Cluster, K-Mean, and Weighted K-Mean. Analyze the best position based on the time. The authors in [26] used the real-time critical healthcare HTH service to determine the best route for the emergency vehicle. IoT sensor installed along the road delivers data about the roads' volume of traffic and the number of existing vehicles. The program creates potential and fastest routes for the ambulance based on this information. [27] describes the development of GSM and cloud-based autonomous traffic signal control for vehicle clearance. The emergency vehicle's GSM module uses an Android mobile application to upload the information to the cloud. Data-driven cloud services and control units adjust the traffic light to make room for emergency vehicles. The majority of these modifications have centered on the sort of power utility that will be employed in this system.

Nevertheless, all the efforts need to be improved to achieve further optimum routes. For this reason, let's select HHO algorithm because the results tested over benchmark functions and several engineering optimization problems confirm that HHO outperforms many well-known Swarm intelligence approaches, such as Particle swarm optimization, Grey wolf optimizer, Genetic programming, Biogeography-based optimization, and Firefly Algorithm [8].

3. The aim and objectives of the study

This work aims to optimize the ambulance vehicle routing using HHO algorithm. To achieve this aim, the following two objectives are accomplished:

– to conduct extensive simulation scenarios;

– to compare our system with counterparts to determine its effectiveness.

4. Materials and methods of research

4. 1. Object and hypothesis of the study

The Object and concept scenario in this study is depicted in Fig. 1.

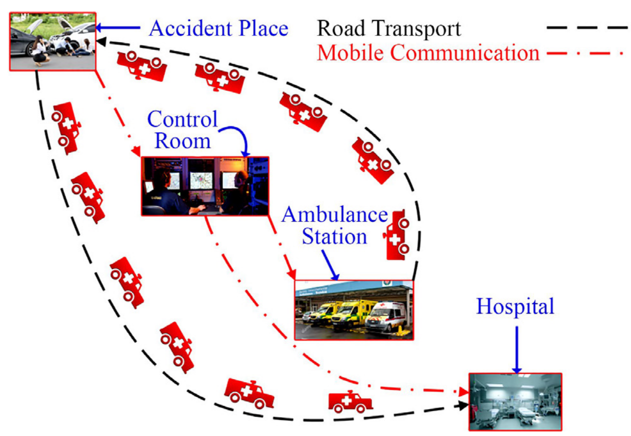


Fig. 1. Ambulance vehicle routing concept scenario

Hypothesis 1.

To request assistance, the control station uses the accident victim or those in the vicinity to determine details about the number and severity of injuries and the accident's location. Employees in the control station communicate with the nearby hospital and ambulance station to inform them of the accident.

Hypothesis 2.

The hospital staff is prepared with the required tools for victims' treatment. Then, the station calls the closer vacant ambulance and provides it with the accident details. The ambulance is headed toward the collision scene and will transport the injured people there for medical attention. In this diagram, mobile communication in ambulance vehicle routing is represented by the dot-dash line, while the dashed line refers to road transport.

Hypothesis 3.

The ambulance station receives accident information from the control station. The precise procedure for routing in the ambulance station is shown in Fig. 2. Regarding the accident site, the ambulance station receives the local map and node details.

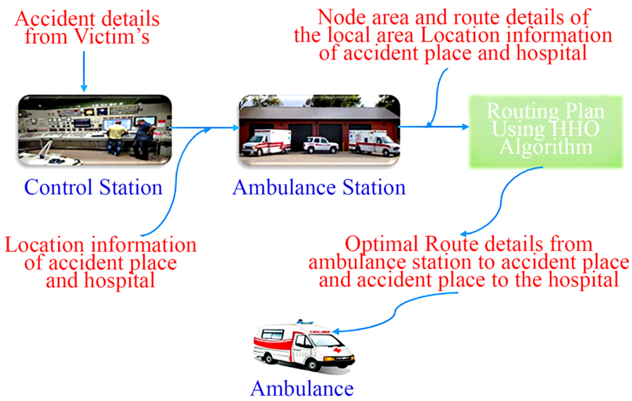


Fig. 2. Ambulance station's ambulance routing procedure

These details are fed into the HHO algorithm to find the ideal paths:

1) the ambulance to the accident;

2) the accident to the hospital.

Sending a route plan to an ambulance via mobile communication is the best option. The ambulance driver should then adhere to the plan as they transport the sufferer to the hospital.

4. 2. Modeling of the routing of the ambulance vehicles using Harris Hawks algorithm

To avoid taking an unnecessary route on the provided route map and reach the objective within a set amount of time and resources, the vehicle must create its route utilizing its intelligent actions. To comply with the above standards, the vehicle should either accelerate on or choose the optimum short path to the destination. The distance between the source and the target should be as small as possible if the ambulance follows the shortest route. The following formula can be used to determine the minimal distance (1):

A formula is part of the text, so the formula must be followed by a semantic sign: if it is followed by a new sentence, then a period; if it is followed by an explanation, then a comma. The punctuation mark must be inside the formula:

$$F1 = distSD(i) = \sqrt{\left[\left(Sx(i) - Dx(i)\right)^2 + \left(Sy(i) - Dy(i)\right)^2\right]}, \quad (1)$$

where, for the current iteration (i), the fitness function is denoted by $F1$, and the dist$SD(i)$ refers to the distance between the source and destination. $x(y)$ coordinates of the source location are denoted by $sx(i)$ $(sy(i))$. Similarly, $x(y)$ coordinates of the destination location are denoted by $Dx(i)$ $(Dy(i))$. When determining the shortest path, the ambulance truck must also consider the undesired route position. If an emergency vehicle takes a wrong turn, it wastes time at the wrong place or adds to the overall process's delay. This makes it necessary for the ambulance vehicle to maintain the greatest possible distance from the wrong turn locations to avoid the situation. Utilizing the distance formula, this maximum distance can be calculated (2).

A formula is part of the text, so the formula must be followed by a semantic sign: if it is followed by a new sentence, then a period; if it is followed by an explanation, then a comma. The punctuation mark must be inside the formula:

$$F2 = distAU(i) = \sqrt{\left[\left(Ax(i) - Ux(i)\right)^2 + \left(Ay(i) - Uy(i)\right)^2\right]}, \quad (2)$$

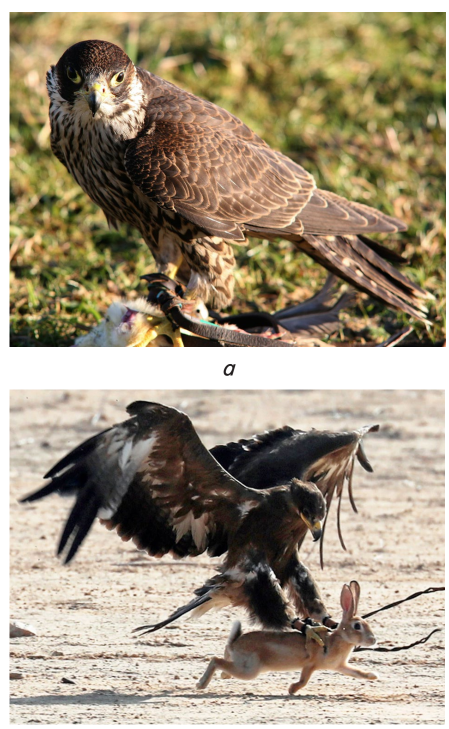
where, for the current iteration (i), the fitness function is denoted by $F2$, and the dist$AU(i)$ refers to the distance between the ambulance and the unwanted place. $x(y)$ coordinates of the vehicle location are denoted by $Ax(i)$ $(Ay)(i)$. Similarly, $x(y)$ coordinates of the unwanted path are denoted by $Ux(i)$ $(Uy(i))$. The following formula represents the fitness (or target) function for ambulance truck routing.

A formula is part of the text, so the formula must be followed by a semantic sign: if it is followed by a new sentence, then a period; if it is followed by an explanation, then a comma. The punctuation mark must be inside the formula:

$$F = F1 + 1/1 + F2. \quad (3)$$

The global path's best local and best global points are identified using the objective function (3). The optimum global direction point is used to establish the new route point for ambulance cars. The loop keeps going till the vehicle reaches the desired location.

An optimization process called group intelligence forces population members to employ both situational and collective knowledge. It makes an effort to fix an optimization problem. Researchers particularly mimic the group hunting behavior for the majority of meta-heuristic algorithms that employ the group intelligence approach. These algorithms involve the population searching for the present prey or ideal position by circling around it and striking when it's appropriate. In nature, many different creatures exhibit group-hunting behaviors (for example, insects, mammals, and arthropods). The activities of various cooperative living entities are included in group intelligence systems, however, their numbers may not be substantial. The falcon optimization algorithm, which was proposed and modeled in 2019, is an illustration of such a system. These birds often hunt in groups of up to six and fly around their target while doing so, as illustrated in Fig. 3.



a

b

Fig. 3. The Harris optimization algorithm's group intelligence hunting mechanism: *a* – observing; *b* – hunting [28]

A formula is part of the text, so the formula must be followed by a semantic sign: if it is followed by a new sentence, then a period; if it is followed by an explanation, then a comma. The punctuation mark must be inside the formula:

$$X(t+1)=\begin{cases} X_{rand}(t)- \\ -r_1\left|x_{rand}(t)-2r_2\cdot X(t)\right| & \text{rand}\geq 0.5, \\ X_{rabbit}(t)-X_M(t)- \\ -r_3\left(LB+r_4(UB-LB)\right) & \text{rand}<0.5. \end{cases} \qquad (4)$$

This adaptation is thought to have been made for desert group hunting without prey. These species behave in a way that suggests a small group advances to begin hunting first. In order to hunt as a group, other group members go ahead and join the hunt. In this manner of hunting, problem-solving solutions (i.e., hawks) disperse around (the best solution) (i.e., the prey). Then, it is hunted by the bird. According to this algorithm, the prey is first recognized, then surrounded, and last assaulted. Each falcon in this algorithm represents a remedy for the issue. The falcons fly toward the direction of the rabbit's position because it is the current best solution. To discover their prey and attack it, falcons must first search the problem space in these methods. The falcons' random and early search actions are quantitatively modeled in (4) [28].

Reflects the current position of a hawk (solution) in the current iteration (t). In the new iteration, the stance that displays the best solution is that of a hawk. The falcon population's center of gravity is located in the problem space, and the variables and show random numbers between 0 and 1, respectively. To determine in the issue space where N Harris Hawks is the number of solutions.

The HHO is used in computing processes since it comprises characterization and choice for an irregular advancement calculation. It ends when efforts are made repeatedly to select the largest number of family members and through the advantageous arrangement of the highlights. It enhances or maintains a facial recognition system's grouping execution.

The fundamental idea behind this computation is the co-evolution of numerous birds rather than focusing on a single type of bird, which adds to strong hunting abilities. Every particle starts out with the requisite qualities, and then each particle's fit attributes are evaluated. The worth of the current fit becomes apparent at that time, and if it is better than the prior one, let's update it as the present worth but leave it unchanged if the old fit's worth is higher. The best feasible arrangement will be reached if this process is allowed to continue.

5. Results of Harris Hawks optimization for ambulance vehicle routing

5. 1. Simulation outcomes and analysis

The experiments were developed in MATLAB on an Intel Core i3 personal computer running at 1.7 GHz. The HHO algorithm's specification is set as in Table 1.

Scenario 1: the simulation results for the first scenario are illustrated in Fig. 4, *a, b*.

Scenario 2: the simulation results for the second scenario are illustrated in Fig. 5, *a, b*.

Scenario 3: the simulation findings for the third scenario are drawn in Fig. 6, *a, b*.

Finally, the cost function of the conducted experiments is shown in Fig. 7.

Table 1

Simulation Parameters

Parameter	Value
Minimum frequency	0
Maximum frequency	0.5
Maximum iterations	100
Pulse rate	0.5
Loudness	0.5
HHO population	100
x coordinate of undesired route location points	1.5, 4.0, 1.2, 8.0, 1.2, 4.8, 4.9, 5.1, 2.8, 5.6, and 7.3
y coordinate of undesired route location points	2.8, 5.6, and 7.3
Dimensions of the undesirable location spots	4.5, 3.0, 1.5, 9.0, 5.6, 4.8, 6.3, 6.5, 8.9, 1.4, and 7.6
Diameter	0.2

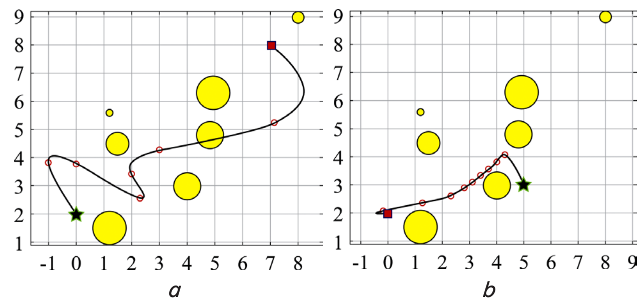


Fig. 4. Simulation findings of scenario 1: *a* – ambulance route to the accident location; *b* – ambulance route to the hospital

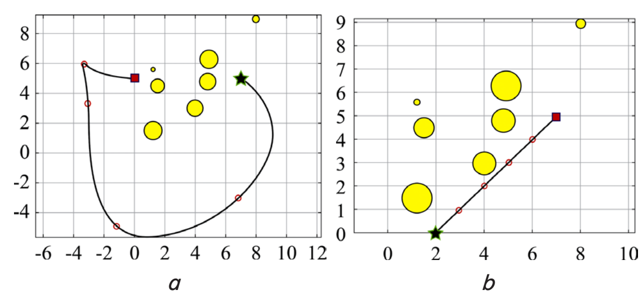


Fig. 5. Simulation findings of scenario 2: *a* – the ambulance route to the accident location; *b* – the ambulance route to the hospital

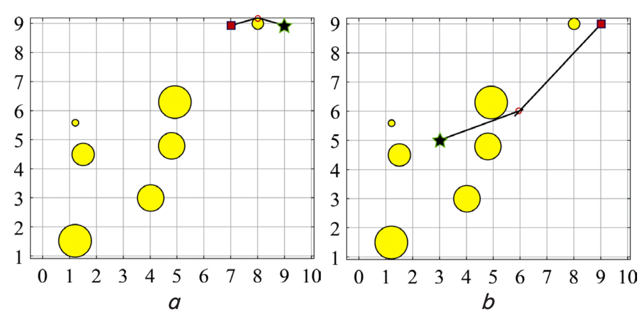


Fig. 6. Simulation findings of scenario 3: *a* – ambulance route; *b* – hospital route from the accident site

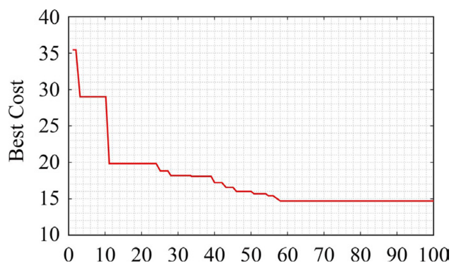


Fig. 7. The cost function of the proposed method

Fig. 7 shows that the best cost initially was 35. When the number of iterations increased, the best cost decreased rapidly to 20 (until iteration 10). After that, the decrease became considerably till the number of iterations reached 60, where the best cost decreased to 15. Next, although the number of iterations increased from 50 to 100, the best cost was kept at 15, which is the minimum cost.

5. 2. Performance evaluation

One hundred vehicles with differing malicious nodes 6, 12, 16, 24, and 30 are utilized to analyze the performance of the HHO. The network is analyzed in the network size with a mobility speed of 12–50 m/s. Let's use TBM [29], TVR [30] and SAODV [31] methods to the effectiveness of the HHO. Here, the performances are analyzed regarding packet delivery fraction, throughput, routing load and end-to-end delay. Table 2 illustrates the evaluation of our proposal.

Table 2

Comparative analysis of HHO

Performances	Methods	Number of malicious nodes				
		8	14	18	26	32
PDF	TBM [29]	0.59	0.50	0.46	0.41	0.30
	TVR [30]	0.85	0.81	0.78	0.69	0.68
	SAODV [31]	0.79	0.71	0.68	0.62	0.58
	HHO	0.91	0.89	0.92	0.88	0.81
Throughput (Kbps)	TBM [29]	151	163	149	152	131
	TVR [30]	149	170	172	164	151
	SAODV [31]	150	159	156	148	146
	HHO	159	181	178	159	162
Routing load	TBM [29]	0.23	0.31	0.80	1.21	1.12
	TVR [30]	0.11	0.16	0.59	1.21	0.89
	SAODV [31]	0.12	0.23	0.69	1.24	1.20
	HHO	0.04	0.09	0.26	0.79	0.89
EED(s)	TBM [29]	0.121	0.121	0.142	0.149	0.176
	TVR [30]	0.10	0.090	0.131	0.150	0.145
	SAODV [31]	0.1	0.126	0.124	0.162	0.156
	HHO	0.004	0.020	0.090	0.121	0.108

In this comparison, the number of malicious nodes is varied between 5, 10, 15, 20, and 25. According to the analysis, the HHO performs better than the SAODV, TVR, and TBM. Improving relay node selection through integrating BA and CNN (i.e., ResNet) is the primary cause for HHO's improved performance. By avoiding malicious nodes while transmitting data packets over the VANET, the packet delivery of the HHO is improved. Accordingly, the successful data transmission resulted in higher throughput for HHO. Since the HHO employs optimal fitness functions during transmission path generation, it does not require a large number of control packets to generate the transmission path. The fitness functions used in the HHO are the distance between source and destination, the distance between ambulance vehicle and unwanted location and trust. Therefore, this HHO achieves less routing load than the TBM, TVR and SAODV. Moreover, the shortest path generation using HHO obtains less EED than the SAODV, TVR and TBM.

6. Discussion of experimental results of Harris Hawks optimization for ambulance vehicle routing

According to the test findings in Fig. 4, *a, b,* (i.e., scenario 1), 8.2 km is the optimum distance between the ambulance station and the accident site. Additionally, 3.6 km is the optimum distance between the accident site to the hospital. Lastly, 63 seconds is the needed time to determine the best route. The results in Fig. 5, *a, b* ((i.e., scenario 2) show the following. 9.1 km is the shortest path between the ambulance station and the accident site. Additionally, 4.6 km is the optimum distance between the accident site to the hospital. Lastly, 62 seconds is the needed time to determine the best route. According to the test findings of scenario 3, in Fig. 6, *a, b,* 2.4 km is the shortest distance between the ambulance station and the accident site. Additionally, 3.6 km is the optimum distance between the accident site to the hospital. Lastly, 40 seconds is the needed time to determine the best route.

The simulation scenarios and verification experiments answered to or research questions:

1. The suggested HHO method generates superior results.
2. In each situation considered, the HHO algorithm system quickly reduced the overall tour distances.
3. It is possible to claim that the HHO algorithm system resists change in the number of locations and the underlying topologies.

According to Table 2, the successful data transmission resulted in higher throughput for HHO. Since the HHO employs optimal fitness functions during transmission path generation, it does not require a large number of control packets to generate the transmission path. The fitness functions used in the HHO are the distance between source and destination, the distance between ambulance vehicle and unwanted location and trust. Therefore, this HHO achieves less routing load than the TBM, TVR and SAODV. Moreover, the shortest path generation using HHO obtains less EED than the SAODV, TVR and TBM.

Consequently, it can be observed that the HHO algorithm consistently produces superior outcomes despite the various significant problem parameters. Furthermore, experiments evaluating performance demonstrated that the HHO algorithm is superior to its counterparts.

Nevertheless, the complexity of the proposal has not been verified. So, it is crucial to determine the complexity using the existing algorithms (such as big O notation). Furthermore, there is a need to use other metaheuristic methods (such as ant colony) to verify and validate our proposal.

Finally, let's believe that using clustering-based ambulance routing strategies may lead to developing and improving the proposal.

7. Conclusions

1. The simulation experiments of the scenarios showed the following. The optimum time needed to find the best routes are 63, 62 and 40 sec for scenarios one, two and three, respectively. Furthermore, the experiments revealed that the best cost function was kept at 15, which is the minimum cost. That is in all scenarios, the system provided shorter total tour distances quickly. Therefore, the proposed method can be argued to be robust to changes in the number of locations and underlying topologies. Accordingly, it can be seen that the HHO algorithm continuously generates better results despite the different significant problem parameters.

2. Performance evaluation experiments demonstrated the superiority of the HHO algorithm over its counterparts (SAODV, TVR, and TBM methods). Furthermore, for ten malicious nodes, the PDF of the algorithm was 0.91, which is higher than the counterparts. The authors recommend using other new metaheuristic methods to improve the system's performance for future works.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Data will be made available on reasonable request.

Acknowledgments

The authors acknowledge the University of Sfax, Tunisia, for their support and assistance.

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