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Research Article

An Intelligent Harris Hawks Optimization Based Cluster Optimization Scheme for VANETs

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In recent years, intelligent vehicles with cutting-edge vehicular applications have grown in popularity, enabling the growth of Vehicular Ad hoc Networks (VANETs). Vehicular Ad hoc Networks (VANETs) are a network of vehicles that share and analyze real-time data and require a well-organized and efficient data delivery method. The stability of clusters and dynamic topology change in VANETs are the major issues in finding an optimal route amongst the vehicles. The cooperative approach and surprise pounce chasing technique of Harris Hawks in nature serve as the main sources of inspiration for Harris Hawks Optimization. In this technique, several hawks work together to attack a victim from various angles to surprise it. Due to the unpredictable nature of situations and the prey's fleeing movements, Harris Hawks can exhibit a variety of intelligent strategies. This study proposes a novel route clustering optimization technique that takes into account communication range, the number of nodes, velocity, orientations, and grid size. To create and evaluate ideal cluster head (CH), the proposed method is based on Harris Hawks Intelligent Optimization Algorithm for route Clustering (iCHHO) which finds optimal and reliable routes amongst the vehicles. Other state-of-the-art methods, such as the Grasshopper Optimization Algorithm (GOA), Gray Wolf Optimization (GWO), and Whale Optimization Algorithm (WOACNET), are utilized to evaluate and validate the proposed method. Our findings show that the developed method outperforms other current methods in terms of number of clusters, variable communication ranges, network size, and the number of vehicles. Furthermore, the statistical analysis concludes that the proposed method improves cluster optimization by 79% and increases cluster stability by an adjusted R-squared of 91.22.

1. Introduction

The world's population is increasing rapidly, with a high reliance on vehicles for traveling, increasing the demand for efficient transportation systems. A recent survey verified this, indicating that the number of passenger and commercial vehicles worldwide has crossed the 1 billion mark [1] and would probably cross 2 billion by 2035 [2]. This increase in the number of vehicles demands that the technology involved in the process also be modified and made flexible according to the vehicle's needs. Certificate distribution and a revocation procedure based on trust thresholds are proposed in [3]. The authors created a trust-based solution by integrating public key certificates with an effective mechanism for certificate revocation and validation. Intelligence needs to be incorporated into the vehicular industry for improving the driving experience, thus increasing passenger safety and accident prevention. This requirement led to the introduction of the concept of Vehicular Ad hoc Networks (VANETs), which is a concept that originated from the Internet of Things (IoT) and has introduced the idea of smart cities and smart transportation. The VANET network assists the drivers by offering road information, current traffic situation, available parking, and better navigation employing route optimization. All this information could be utilized to organize traffic in cities and help minimize life-threatening risks involved in driving and security. The suggested method implements a simple security methodology for completely distributed trust-based public key management for VANETs. By employing a trust-based strategy rather than strict security restrictions to close security flaws, this work intends to maximise efficiency [4].

VANETs involve real-time processing data that might be critical, so the VANET networks must be practical and robust enough to meet these requirements. This critical and real-time nature of the data also demands data security and low latency requirements to deliver the data in time to the users securely [5]. Different routing protocols and mechanisms have been proposed by various researchers for the VANET networks. These research efforts further be improved, and existing issues of the VANET networks can be optimized by introducing machine learning reinforcement learning and nature-inspired algorithms [6]. Bioinspired methods focus on different optimization problems at the elementary stage for realistic applications, including routing in VANETs [7]. Various bioinspired methods exist in the literature inspired by fishes, ants, birds, dolphins, etc.

IoV derives by merging two main concepts, IoT, and VANETs (as shown in Figure 1), with a vision to provide an intelligent vehicular system that tackles various issues, such as effective accident avoidance, road congestion, driver assistance, routing, and safety. In the following, briefly explain the IoV concept for novice readers.

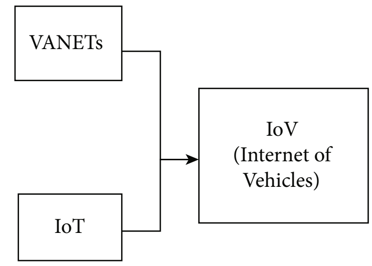

Figure 1: Composition of IoV [8].

1.1. Vehicular Ad Hoc Networks. Vehicular Ad hoc Networks (VANETs) are an emerging idea in the transportation industry that intends to add intelligence to the current vehicular networks [8]. It evolved from VANETs to address the present limitations of VANETs, such as incompatible personal devices, unreliable wireless internet, and a lack of commercialization [9, 10]. In VANETs, there are various communications links such as intervehicular, intravehicular, vehicle-to-infrastructure (V2I), vehicle-to-roadside units (V2R), vehicle-to-sensors, (V2S), and vehicle-to-person (V2P) [11–13].

There are mainly three different types of mobile technologies listed below to establish these links [14]:

(1) Dedicated short-range communications (DSRC) and communication access for land mobiles (CALM) technologies

(2) Satellite technologies, 4G/LTE, and WiMax

(3) Zigbee, Wi-Fi, and Bluetooth technologies for short-range

Figure 2 depicts the overall structure of a VANET network, consisting of vehicles, roadside units, sensors, and network infrastructure. The communication links between these elements are also shown, particularly V2V, V2R, V2P, V2S, and V2I. Every node is integrated with an On-Board unit (OBU), equipped with sensors that collect data from the environment. Because the VANET network generates data for essential information, it uses a variety of intelligent technologies to process it.

Next, we present the basic concept of bioinspired algorithms and their applications in VANET networks.

1.2. Bioinspired Algorithms in VANET Networks. Various features and applications of VANETs have enhanced the performance and further strengthened the existing ITS. However, different challenges and issues have also been raised to implement the VANETs technology. In this context, multiple studies focus on various essential features of vehicular networks such as routing, safety, and space administration. Recently, bioinspired methods have been introduced to improve existing frameworks of ITS. The inspiration of this paper is to seek the opportunity of using and deploying evolutionary methods to find optimized solutions to some of the following problems in VANET networks:

(1) Nature-inspired algorithms are more efficient and effective in networks like VANETs because species' actions to search for food or fulfill other natural needs are similar to finding the best route in the VANET networks [15]. Nature-inspired algorithms also help to achieve route optimization with zero to minimal human intervention [16]. Also, nature-inspired algorithms ensure optimal routing in different network scenarios and improve the robustness of the VANET networks

(2) Nature-inspired algorithms are self-organized and adaptable to various situations, and hence, they effectively deal with different types of topological structures of the VANET networks

(3) Nature-inspired algorithms have better accuracy in sensing the network's damage nodes as they integrate a maximum degree of exploration and exploitation. This provides an effective way of reducing security attacks on the network and hence enhances the network's security [17]

(4) Another advantage of employing bioinspired methods is their low complexity in solving computational problems of the VANET networks

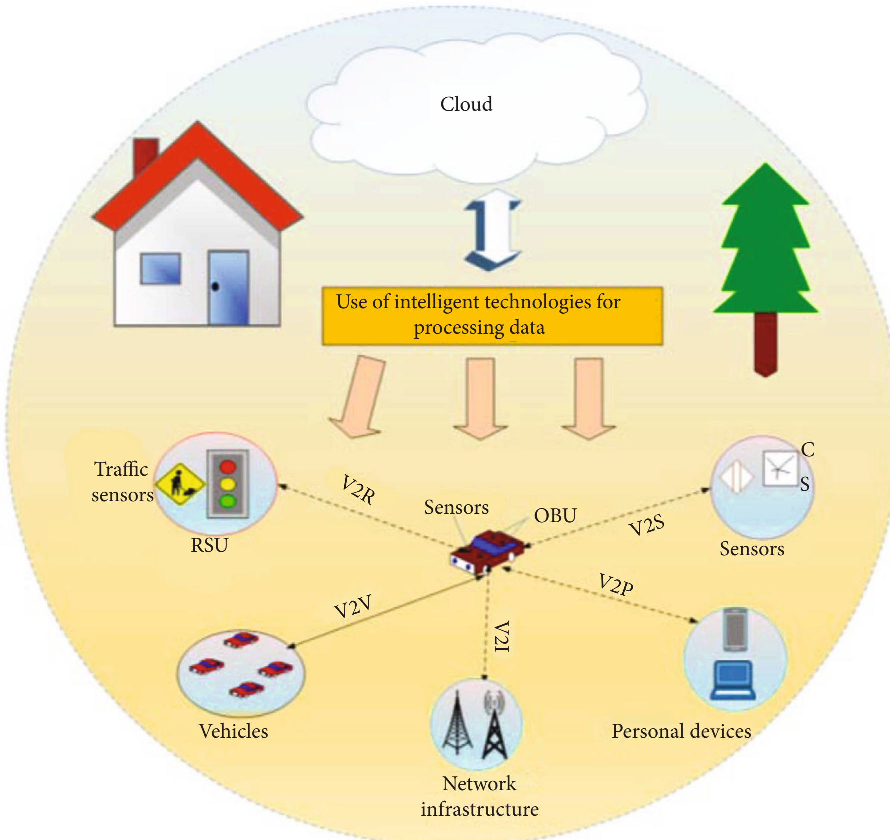

Figure 2: General structure of VANET network [9].

1.3. Contributions. Based on the above advantages of bioinspired algorithms, this study proposes an intelligent Harris Hawks Optimization to optimize clusters in VANET networks. The first phase of the proposed algorithms performs the searching of vehicles, creating a topology by incorporating self-adjusted weights to minimize the error. In the next phase, based on the individual fitness function of hawks, the selection of cluster heads is accomplished for the management of the network to enhance accuracy. The main contributions of the paper are summarized as follows:

(1) This research presents a novel intelligent Harris Hawks Optimization for cluster optimization in VANET networks

(2) An objective clustering is introduced in which each objective is given a weight based on the fitness function of each vehicle

(3) Self-adopted weights have been deployed to minimize randomness amongst the vehicles, thus minimizing error

(4) The performance of the developed Harris Hawks clustering optimization algorithm has been evaluated by performing statistical tests such as ANOVA, p -test, and regression coefficients by deploying FMOLS statistical test

(5) For the developed method, comparative analysis for various network parameters, such as transmission range, grid size, node density, and load balance factor was conducted for evaluation by incorporating dynamic network nodes

1.4. Organization. The organization of the remaining article is as follows: In Section 2, recent trends in VANETs and different nature-inspired clustering optimization methods are reviewed. Section 3 presents the proposed method, including mathematical modeling followed by experimentation and results in Section 4. Section 5 presents the statistical analysis for the evaluation of the developed method. Section 6 presents the conclusion and future work.

2. Related Work

Bioinspired algorithms are used in many applications such as the Internet of Things [18], image processing [19], agriculture [20], healthcare [21], and security [22]. Recently, these algorithms have provided effective solutions regarding routing, safety, and efficient parking for vehicular networks.

The major role of routing in the VANET networks is the broadcast of messages across the vehicles regarding emergencies, accidents on the roads, or current road situations [16]. Hence, routing needs to be performed effectively in the VANET networks so that the real-time critical data could be distributed efficiently on time. Different evolutionary algorithms have been proposed to achieve routing in VANETs; nature-inspired algorithms are the most promising by optimizing the routes efficiently and effectively. These bioinspired methods for routing in VANET networks are described below:

2.1. Particle Swarm Optimization (PSO). PSO is a well-known nature-inspired algorithm based on the concept of a group of fishes and birds. This concept is also used in VANET networks recently to optimize vehicle routes. For instance, a clustering routing based on PSO (CRBP) is proposed in [23] for finding optimum routes in VANETs. The CRBP comprises three steps, i.e., the formation of clusters, the coding of route particles, and optimum routing. In the first step, nodes with similar directions are identified. Then, cluster heads are selected, and different constraints such as node location, speed, and neighbors are used to construct stable clusters. Once a cluster is constructed, the fitness of the link is calculated to help in finding the best router quickly. Another PSO algorithm named FPSO is proposed in [24] for optimal route discovery in VANETs [24]. The clustering of the vehicle nodes in the FPSO algorithm is performed using multiple features such as the energy level of the vehicle, the number of neighbor vehicles, and the distance from the base station. FPSO is stable and more reliable for route selection of delivery of packets in the network because the transmission links are selected based on fuzzy logic, which helps avoid link failures. Rajawat et al. proposed another PSO algorithm named CH-PSO with a novel strategy of finding a cluster head in different scenarios of VANETs [25]. The proposed algorithm splits the road into two lanes after presuming the size of the network. After splitting the highway, clusters of vehicles are formed by placing vehicles and RSU. Now, automobile with the maximum capacity value is designated as the head of the cluster using the PSO algorithm, and this cluster head starts forwarding the data to the RSU.

2.2. ANT Colony Optimization (ACO). As its name suggests, Ant Colony Optimization (ACO) gets inspiration from the pattern of ants searching for food and using the shortest path. For instance, the F-ANT protocol is proposed in [26] based on the ACO algorithm for VANET networks. This protocol relies on fuzzy logic to compute the reliability of the routes. Different fuzzy criteria are defined where the bandwidth defines the node's capability to provide packet transmission services. Since VANET networks have a high mobility rate, the Received Signal Strength Metric (RSSM) is used to define the connectivity level of intermediate links, whereas Congestion Metric (CM) is used to measure the congestion value of the route's links. The advantage of the F-ANT protocol is that road safety is guaranteed, making it suitable for urban scenarios. The disadvantage is its vulnerability to various security threats. However, this protocol was extended to be used in freeways and added a provision for data safety. Then, Li et al. proposed Adaptive Quality of Service-based routing protocol for VANETs (AQRV) [27], based on the ACO algorithm. The AQRV introduces the concept of interconnection routing, where data messages choose self-adjustment connections for data transfer to the destination. This protocol works in two steps, i.e., electing a robust connection and creating the best route. The terminal intersection is aimed at minimizing the congestion in the network and improving the exploration time of routes. Another protocol named Local QoS Models (LQMs) has also been proposed based on ACO to reduce network congestion in one-lane road segments. The advantage of the LQMs protocol is that it provides better performance than other existing routing protocols.

Another ACO algorithm-based solution, named QoRA, has been proposed in [28], which follows the QoS routing approach and is aimed at improving routing in ad-hoc networks by avoiding network congestion during the transmission. QoRA protocol consists of two main components: SNMP unit and QoRA unit, where the QoRA entity is run on each node to identify suitable paths while SNMP unit further comprises two components. SNMP manager is used to providing needed data for QoS, and MIB is the management information base. Goudarzi et al. proposed an Efficient GSR protocol (EGSR), an ACO-based traffic-aware routing protocol [29] that makes the vehicles evaluate the street connectivity in their neighborhood utilizing small-sized control data units. These packets are broadcasted using an effective dissemination procedure in a controlled broadcast storm. The main advantage of the GSR protocol is that it does not use any additional hardware such as RSU or traffic sensor at different junctions. Kazemi et al. proposed an Opposition-based ACO (OACO) algorithm for routing in the VANETs [30], which uses the concept of computing opposition in ACO, and hence, diverse areas of solution space are discovered.

2.3. Genetic Algorithms (GA). Another approach used by researchers to find the optimal solution for routing based on natural processes is Genetic Algorithms (GA). Zhang et al. designed and proposed GABR (GA-based routing protocol) with QoS perception for VANETs [31]. GABR comprises GPS and Intersection Based Routing protocol (IBR). First step in this is another approach used to find the optimal solution of routing based on natural processes which is Genetic Algorithms (GA). For instance, Zhang et al. proposed a GA-based routing protocol (GABR) with QoS perception for VANETs [31]. GABR comprises GPS and Intersection Based Routing protocol (IBR), where the first step involves searching the existing paths using IBR protocol. The route with optimal QoS is chosen using GA through five steps from all the available routes. Amongst the five steps, the first step is to avoid route circulation, then to initialize the population in which the preliminary population is searched as routes. The next step is selection, in which the individual with a maximum fitness cost is nominated, followed by a crossover in which subpaths of two individuals are exchanged. The final step is a mutation in which the mutation operator is used to select a solution from the population. The results of this GABR protocol show that it performs better than other protocols, such as IBR or CAR protocols. However, it is disadvantageous because it is slower and more complex. Gupta and Kumar have suggested a genetic protocol-based routing and spanning trees for routing in VANETs [32]. The proposed algorithm works in three different phases. In phase 1, also known as GA, each node's fitness value is computed and used to find the optimal route. In phase 2, a spanning tree of the fitness value of each node, calculated in the first phase, is constructed. This tree helps get rid of the links that make a loop and make the paths with no loop. In phase 3, the spanning tree is constructed from the routing tree, making well-organized additions and removals and storing all the nodes' required information.

2.4. Firefly Algorithm. As its name suggests, the firefly algorithm takes its motivation from the patterns of fireflies for performing different activities. In the context of VANET networks, Reference [33] proposed FF-L, a levy-distribution-based firefly algorithm for multicast routing where the FF algorithm utilizes an arbitrary exploration in case of no brighter FF at the time of inquiry. The FF-L algorithm combines levy distribution to avoid local minima. The levy flight is a random move in a specific direction, and this impulsive change is deployed to improve the span of the exploration process. To its advantage, FF-L is quick and robust and works reliably well to solve the problems in multicast routing when compared to other algorithms. Then, Sabharwal et al. proposed EFR, a firefly-based efficient and reliable routing protocol for routing in VANETs [34]. This proposed algorithm works in two steps: route discovery and the EFR technique. EFR depends on the firefly next-hop election method for route discovery. Each request data unit for the route contains coordinates of the destination and its location and the transmitter and receiver addresses. EFR technique starts finding a path to find the best direction, and once the best path is found, the data units are communicated via an established path. The key benefits of this protocol are its better performance over dynamic source routing (DSR) in terms of end-to-end delay, throughput, and packet delivery ratio.

2.5. Other Nature-Inspired and Clustering Algorithms for VANETs. Some of the other recent studies proposed similar optimization techniques for cluster head nomination in vehicular networks are Whale Optimization [35], Grasshopper Optimization [36], Grey wolf Optimization [37], CLPSO, MOPSO [38], ALO [39], ACO [40], CAMONET [41], CAVDO [42], and i-WOA [43]. These optimization techniques for VANETs are derived from biological and evolutionary computation by taking inspiration from birds, ants, moth flames, Harris Hawks, dragonflies, etc. Some of the recent route clustering algorithms for VANETs include AODV based energy efficient algorithm [44], Q-learning algorithm-based IoT network for user privacy [45], fuzzy logic-based routing [46], forward aware energy-based routing method [47], RFID-based anticollision method [48], coverage based routing [49], transmission improvement based on OLSR protocol [50], multihop passive clustering algorithm [51], delay-tolerant based Vehicles of Interest algorithm [52], offloading scheduling method based on energy consumption [53], fuzzy neural network- (FNN-) based data missing estimation in IoV [54], link lifetime-based routing [55], and deep reinforcement learning-based routing [56]. Based on these studies, in the next section, we propose an intelligent clustering technique that utilizes Harris Hawks Optimization.

3. Proposed Technique

This section provides clustering and cluster head formation techniques by deploying Harris Hawks Optimization for the vehicular environment by taking inspiration from the chasing pattern of Harris Hawks. The proposed method starts with the initialization of vehicles on the highway (exploration phase). Once all the vehicles are registered with the network containing their speed, direction, acceleration, and position, the clustering process (exploitation phase) is initiated based on the fitness function of each vehicle and the cluster head is selected.

3.1. Intelligent Clustering via Harris Hawks Optimization. Harris Hawks Optimization is a nature-inspired population-based innovative problem-solving method that performs intelligent clustering deploying (iCHHO) for VANET networks [57]. Due to its simplicity and easy implementation process, it could be utilized for tackling many problems such as route-finding, cluster-based routing, and route optimization between vehicles. The flowchart of the developed iCHHO is given in Figure 3. In the following, we explain the different steps of the proposed algorithm.

3.1.1. Exploration Phase. In the exploratory phase, the cluster head (CH) searches for the target (vehicle) in a defined network size, where CH detects and tracks other vehicles randomly. Sometimes, it takes time to detect and locate other vehicles due to speed and random movement of vehicles. Therefore, the vehicle (CH) must have to observe, monitor, and wait for some time to detect the targeted vehicle on the highway. In iCHHO, all vehicles are the candidate solution in a search space, and the CH is the best candidate solution obtained after evaluating of a fitness function. Two strategies have been used in iCHHO to detect vehicles on the highway. First, the position of all vehicles is determined, and in the second phase position of the cluster head is obtained by using

$$Y(I_i+1)=\begin{cases} Y_{\text{rand\_hawk}}(I_i)-R_1\left|Y_{\text{rand}_{\text{hawk}}}(I_i)-2R_2Y(I_i)\right| & Q\geq 0.5, \\ \left(Y_{\text{rabbit}}(I_i)-Y_{\text{avg}}(I_i)\right)-R_3(\text{lower}+R_4(\text{upper}-\text{lower})) & Q<0.5, \end{cases} \tag{1}$$

where $Y(I_i+1)$ represents the location vector of vehicles in the subsequent repetition I_i, $Y_{\text{rabbit}}(I_i)$ shows vehicle position, $Y_{\text{avg}}(I_i)$ presents vehicles present location, R_1, R_2, R_3, R_4, and Q are random numbers to switch between exploration and exploitation phases, respectively, and are set between 0 and 1, upper represents an upper bound of variables and lower is lower bound of variables, and $Y_{\text{rand}_{\text{hawk}}}(I_i)$ represents randomly nominated cluster head vehicle from the present search space.

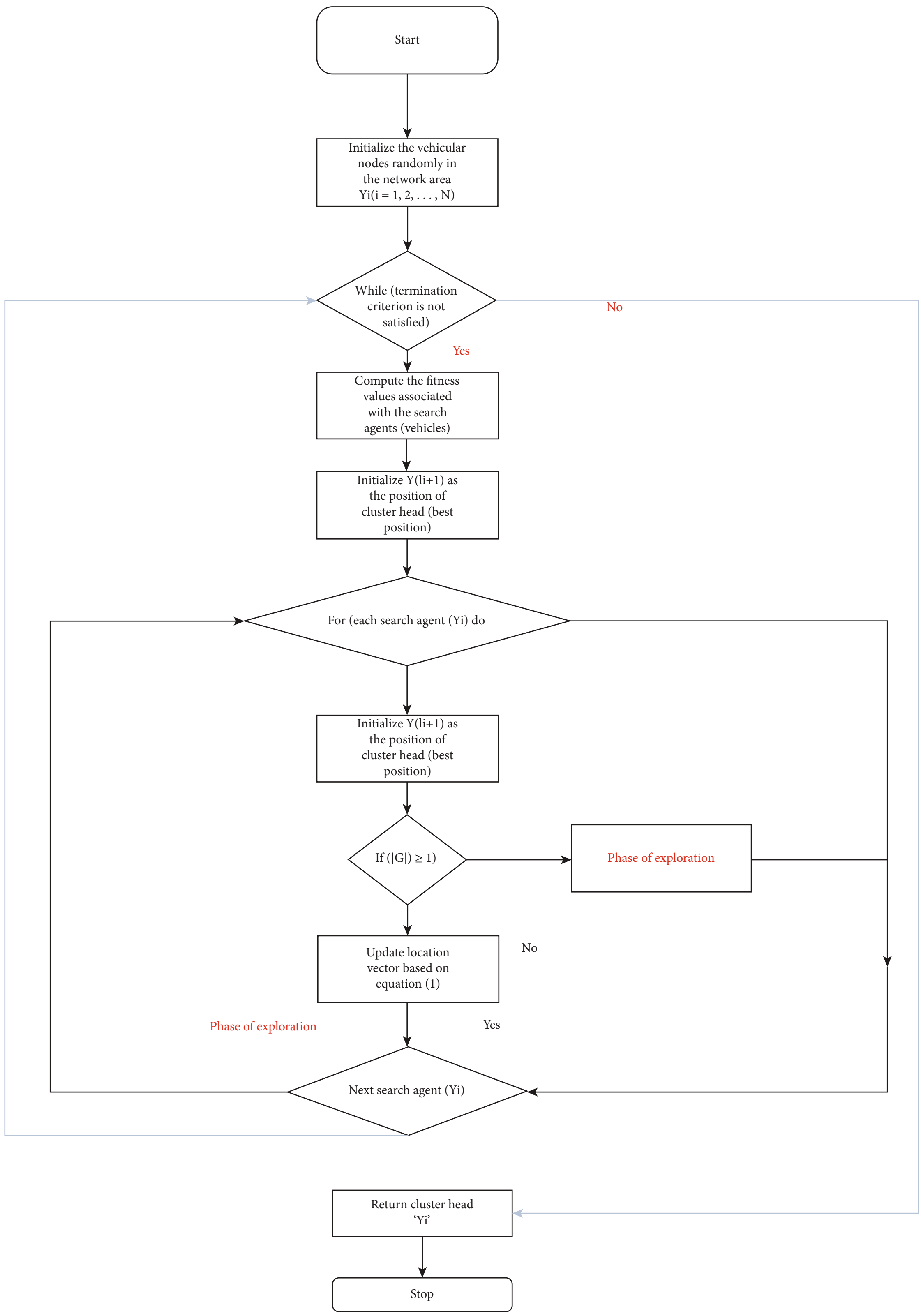

Figure 3: Flowchart of the proposed iCHHO algorithm.

The average location of vehicles is attained as

$$Y_{\text{avg}}(I_i) = \frac{1}{N}\sum_{i=1}^{N} Yi(I_i), \tag{2}$$

where Y_{avg} shows the mean location of present vehicles' search space, Y_i shows the vehicle's current position, I show the current iteration, and N is the total population size.

3.1.2. Evolution from Exploration to Exploitation. When the target vehicle energy is low, it could be easily exploited. The vehicle's energy decreases while escaping from the cluster head. In the beginning, the vehicle's energy level is high. However, when a cluster head is chasing the vehicle to be part of a cluster, its energy decreases gradually. The energy level of the vehicle is calculated as

$$G = 2Go\left(1 - \frac{I_i}{T}\right), \tag{3}$$

where G shows the losing energy of the vehicle, G_0 represents starting state of its energy inside the interval [-1,1], T represents iterations (maximum), and I represent the current iteration.

The cluster head continuously chases other vehicles, due to which the power of the target continuously decreases. Energy level G_0 decreases from 0 to -1 which shows that the vehicle energy is low. However, when the value of G_0 becomes 1 from 0, showing that the target energy is strengthening and has the potential to detach itself from a cluster. Consequently, depending on the value of G, iCHHO switches between the exploration and exploitation phases.

3.1.3. Exploitation Phase. As discussed above, the exploitation phase happens only when $|G| <1$. In this phase, all vehicles in a network perform the surprise formation to be the cluster head. However, some vehicles still try to escape from the formation of the cluster. Therefore, the chosen cluster head performs different chasing strategies that could happen in a real situation. Four strategies have been proposed in iCHHO to represent the cluster head's attack on all the vehicles in a given search space depending on the location, position, speed, and direction of vehicles. It is supposed that vehicles always try to escape from the cluster head which is donated by r. However, the CH would try to catch the vehicle by performing a soft or hard besiege. It means that the CH will form a ring around the vehicles and surround it with diverse angles gently or hardly relying on the residual energy of the CH. However, in an actual environment, a CH becomes nearer in the direction of the projected target to raise the likelihoods to vehicles cooperatively by the use of surprise pounce. After some interval of chasing vehicles, CH would lose its energy rapidly, and a CH could capture the target by using one of the encircling processes. The soft besiege will happen when $|G| \geq 0.5$, and the hard besiege takes place when $|G| <0.5$.

(1) Soft Besiege. When $r \geq 0.5$ and $|G| \geq 0.5$, it meant the vehicle has enough remaining energy to disappear from a CH where r represents the ability of vehicles to escape joining a cluster. In this strategy, the CH surrounds the vehicles softly from different angles to reduce the escaping energy of all vehicles to perform a technique (surprise pounce). This behavior is modeled as

$$Y(I_i + 1) = \Delta Y(I_i) - G\left| Y_{\text{jump}_{\text{rapid}}} Y_{\text{rabbit}}(I_i) - Y(I_i)\right|, \tag{4}$$

$$\Delta Y(I_i) = Y_{\text{rabbit}}(I_i) - Y(I_i), \tag{5}$$

where $\Delta Y(t)$ vectors are variance vectors between the location route of the target and present position, $Y_{\text{jump}_{\text{rapid}}}$ is the CH's rapid jump strength, and Y_{rabbit} is the CH position. The value of the Y varies randomly in every step to pretend the vehicle's nature.

(2) Hard Besiege. When $r \geq 0.5$ and $|G| <0.5$, the target vehicle's speed and its remaining energy are low to escape from the CH. Similarly, the CH uses hard besiege to enclose the projected target (vehicle) to execute a surprise attack. Here, the current position is updated as

$$Y(I_i + 1) = Y_{\text{rabbit}}(I_i) - G|\Delta Y(I_i)|. \tag{6}$$

(3) Soft Besiege with Progressive Rapid Dives. When $|G| \geq 0.5$ and $r < 0.5$, vehicle has enough energy to get away from the cluster head, and a soft besiege is executed to reduce the energy of the vehicle. This mechanism is considered intelligent compared to the preceding one. To model the technique of escaping of vehicle and leapfrog movement, the levy flight (LF) [33] concept is employed in the iCHHO algorithm. The LF concept is utilized to duplicate the misleading movement of the prey for the duration of escaping stage and asymmetrical, unexpected, and quick dives of the attacker across the escaping vehicle.

A collection of vehicles rapidly surrounds other vehicles to accurate their location and route regarding the misleading motions of the vehicle. The LF-based scheme is the leading probing mechanism for the predator in constructive searching environments. Additionally, the LF-based ideas have been detected in sharks and monkeys within the chasing activities. According to the actual behavior of the vehicles, it is considered that vehicles regularly select the optimal cluster head in the direction of the vehicles once they need to follow the vehicles. Hence, to implement a soft encircling, it is assumed that the next move of the cluster head is estimated by employing the following rule.

$$\text{Pin}_Y = Y_{\text{rabbit}}(I_i) - G|\, Y_{\text{jump}_{\text{rapid}}} Y_{\text{rabbit}}(I_i) - Y(I_i). \tag{7}$$

Compare the current location with the previous one, and take a look at whether its encircling mechanism was good enough to attach other vehicles with itself. If the current dive is found not fair, in addition, they begin irregular, sudden, and speedy dives when an approach the prey. We assume that the vehicles would move on the highway depending on LF-based forms by utilizing the subsequent rule:

$$\mathrm{Pin}_Z = \mathrm{Pin}_Y + V_{1\_\mathrm{Dim}} * L_{FF}(\mathrm{Dim}) \tag{8}$$

where Dim shows the size of the problem and V_{1_Dim} represents random vector by size $1 \times \mathrm{Dim}$ and L_{FF} is the LF function, obtained as [33]

$$L_{FF}(V_{1\_\mathrm{dim}}) = 0.01 * \frac{u * \partial}{|v|^{1/\beta}}, \tag{9}$$

where

$$\partial = \left(\frac{\tau(1+\beta) * \sin(1/\beta)}{\tau(1+\beta/2) * \beta * 2(\beta - 1/2)}\right)^{1/\beta}, \tag{10}$$

where u and v represent random values between [0,1] and β shows a constant value of 1.5. Consequently, the last approach for upgrading the locations of all vehicles in the soft encircle is performed as

$$Y(I_i + 1) = \begin{cases} \mathrm{Pin}_Y & \text{if } F(\mathrm{Pin}_Y) < F(Y(I_i)), \\ \mathrm{Pin}_Z & \text{if } F(\mathrm{Pin}_Z) < F(Y(I_i)). \end{cases} \tag{11}$$

(4) Hard Besiege with Progressive Rapid Dives. When $|G| < 0.5$ and $r < 0.5$, the remaining energy of the vehicle is not enough to skip from the network grid. Consequently, a hard besiege strategy is set up earlier than the surprise CH to capture and join other vehicles. Both the steps (soft and hard) are the same in this situation on the vehicle side. However, this time the CH will try to decrease the gap of their mean position with the running vehicle. Hence, the following rules are accomplished in this situation:

$$Y(I_i + 1) = \begin{cases} \mathrm{Pin}_Y & \text{if } F(\mathrm{Pin}_Y) < F(Y(I_i)), \\ \mathrm{Pin}_Z & \text{if } F(\mathrm{Pin}_Z) < F(Y(I_i)), \end{cases} \tag{12}$$

where Pin_Y and Pin_Z are calculated as

$$\begin{aligned} \mathrm{Pin}_Y &= Y_{\mathrm{rabbit}}(I_i) - G\left|Y_{\mathrm{jump}_{\mathrm{rapid}}} Y_{\mathrm{rabbit}}(I_i) - Y_{\mathrm{avg}}(I_i)\right|, \\ \mathrm{Pin}_Z &= \mathrm{Pin}_Y + V_{1\_\mathrm{Dim}} * L_{FF}(\mathrm{Dim}), \end{aligned} \tag{13}$$

where $Y_{\mathrm{avg}}(I_i)$is obtained using (2) and Pin_Y or Pin_Z would be the subsequent position for the next repetition.

3.1.4. Complexity Analysis of iCHHO. The initialization of vehicles, the fitness assessment of each vehicle, and the updating of cluster heads are the three operations that have the most impact on the computational complexity of the Harris Hawks Optimization for cluster optimization in vehicular networks. The computing complexity of the initialization step is O for N vehicles (N). The best position is sought after, and the location vectors of all vehicles are updated. The computational complexity of the updating process is $O(TN) + O(TND)$, where T is the maximum number of iterations and D is the dimension of particular problems. As a result, iCHHO's computational complexity is $O(N(T + TD + 1))$.

4. Results and Discussion

This section provides the simulation results by considering diverse network parameters, such as transmission range, number of vehicles, network size, and load balance factor. After modeling the developed method, simulations and experimentations have been performed, and obtained results are compared with well-established benchmark methods, i.e., WOACNET [35], GWO [37], and GOA [36], respectively. The proposed method and algorithms mentioned above have been implemented in MATLAB with GPU settings (Octave Library) and Google Colab simulation setup. The basic simulation parameters considered are presented in Table 1.

4.1. Transmission Ranges vs. Number of Clusters. The next step is to evaluate the proposed method to generate an optimal number of clusters for a dynamic number of nodes 30, 40, 50, and 60 by taking a 1 km ∗ 1 km network size and communication range from 100 m to 600 m. As clear from the theoretical analysis, the lesser the communication range, the greater the number of clusters will be. Figure 4 shows that the number of cluster heads decreases by increasing the communication range. For all vehicle classes, the iCHHO performs effectively by generating a small number of clusters at a low cost. When the number of nodes is set to 30, iCHHO produces the minimum number of clusters. However, when the number of nodes is increased from 40 to 60, iCHHO performs considerably better; the results of *i*CHHO at some point overlap with other methods due to the algorithms' random nature. The results in Figure 4 present the dominance of developed iCHHO over other well-established methods GWO [37], WOACNET [35], and GOA [36] in terms of optimized clusters for different communication ranges.

4.2. Network Nodes vs. Number of Clusters. In Figure 5, for a better understanding, the results are presented from a different angle, with a number of nodes linked to a number of clusters, transmission range raised from 300 m to 600 m, and network size kept at 1 km ∗ 1 km. It is observed that when the transmission range is set at 300, the number of clusters generated is considerably higher for all the established methods. However, iCHHO is still producing a minimal number of clusters as compared to other methods. The trend could be observed for transmission range = 400, 500, and 600 m. An interesting phenomenon was observed; the number of clusters decreases as the transmission range increases from 300 to 600 m. Also, the iCHHO is performing better and producing an optimal number of clusters compared to other methods.

4.2.1. Grid Size vs. Number of Clusters for 30 and 60 Nodes. The results shown in Figures 6 and 7 are from a different perspective where the network nodes in Figure 6 are kept

Algorithm 1: Algorithm of the proposed *i*CHHO
1. Initialization of each vehicle position, direction, and speed on the highway randomly
2. Creation of mesh topology among vehicles and assigning a vehicle id
3. Calculation of distance of vehicle with others, normalization, and association of these distances in a mesh topology.
4. Initialize the random Vehicles population $Yi(I_i)$ (i=1, 2, . . ., N)
5. While (present repetition< maximum number of repetitions) do
6. Calculate the fitness values of vehicles
7. Set Yrabbit as the location of the vehicle (cluster head)
8. for (each vehicle ($Yi(I_i)$)) do

Update the initial energy G_0 and energy strength Y_{jump_rapid}

G_0=2 random ()-1, Y_{jump_rapid}=2(1-random ())

Update the G using $G = 2Go(1 - (I_i/T))$

if (|G|≥1) then

Update the vehicle's present location by using eq.(3)

if (|G| < 1) then

if (r≥0.5 and |G|≥0.5) then **Soft encircle**

Update the vehicle's present location by eq. (4)

else if (r≥0.5 and |G| <0.5) then **Hard encircle**

Update the vehicle's present location by eq. (6)

else if (r <0.5 and |G|≥0.5) then **Soft encircle with advanced quick dives**

Update the vehicle's present location by eq.(11)

else if (r <0.5 and |G| <0.5) then **Hard encircle with advanced quick dives**

Update the vehicle's present location by eq. (12)

9. Return Yrabbit

Algorithm 1: Presenting the algorithm of the developed mathematical model.

Table 1: Simulation parameters.

Parameters	Values
Population size (Hawks)	100
Maximum iterations	350
Vehicle velocity	22 m/s-30 m/s
Network size	1 km ∗ 1 km
Search plane	2D
Communication range	200 m-600 m
Mobility model	Freeway mobility model
Simulation runs	10
Weight 1 & weight 2	0.5
Convergence factor	0.001
Nodes	30-60

constant, i.e., 30 for dynamic transmission range, and the results are equated by plotting network size on the X and the cluster heads on the y-axis. According to the proposed algorithm, the number of cluster heads grows as well, and the two have a direct relationship when the grid size grows. iCHHO outperforms other state-of-the-art algorithms, as evidenced by the findings. Similarly, the same experiment is carried out with the number of nodes set to 60, as shown in Figure 7, and it is clear that iCHHO outperforms the other methods [35–37] from this perspective as well.

4.3. The Load Balance Factor (LBF). Load balance factor (LBF) is deployed as an evaluation technique to compute cluster head load [37]. The cluster head should ideally be responsible for an equal number of cluster nodes; however, maintaining a consistently load-adjusted architecture is exceedingly difficult due to the rapid changes in the topology of the VANETs environment. In terms of modifying the load in the network, iCHHO outperforms GWO, WOACNET, and GOA as the number of neighboring nodes approaches its maximum value by taking 30 nodes for a 1 km ∗ 1 km grid size could be seen in Figure 8. The result illustrates that the proposed method manages an optimized number of nodes in a single cluster compared to other well-established methods.

The same experimentations have been performed in Figure 9. However, this time number of nodes is increased to 60 to check the efficacy of the proposed method. It is evident from Figure 9 that iCHHO outperforms other benchmark methods by balancing the network load more efficiently.

According to the findings in Figure 4, iCHHO initially produces 26 clusters for 30 nodes with a network size of 1 km ∗ 1 km and 45 clusters when the number of nodes is increased to 60, with a transmission range of 100 to 600 meters. The thorough analysis demonstrates that the newly developed method outperforms other methods mentioned in [43–56]. Additionally, an interesting correlation between the communication range and the cluster number has been found; as the communication range grows, iCHHO creates more optimal clusters. In Figure 5, experiments were carried out by comparing the number of clusters to the number of network nodes while maintaining a 1 km by 1 km grid and varying the communication range from 300 to 600 m. The findings demonstrate that the method developed generates the ideal number of clusters as compared to WOACNET, GOA, and GWO.

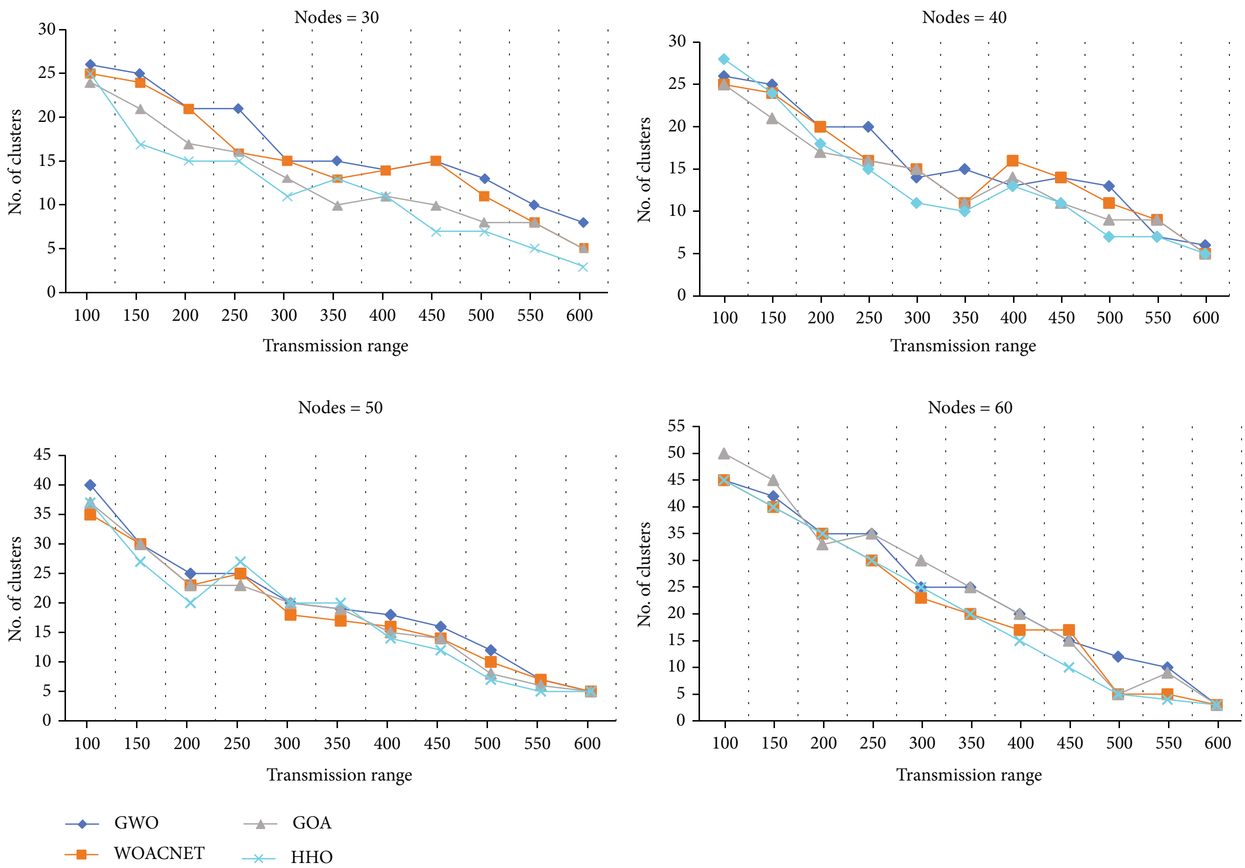

Figure 4: Transmission range vs. number of clusters for 30-60 nodes and network size of 1 km × 1 km.

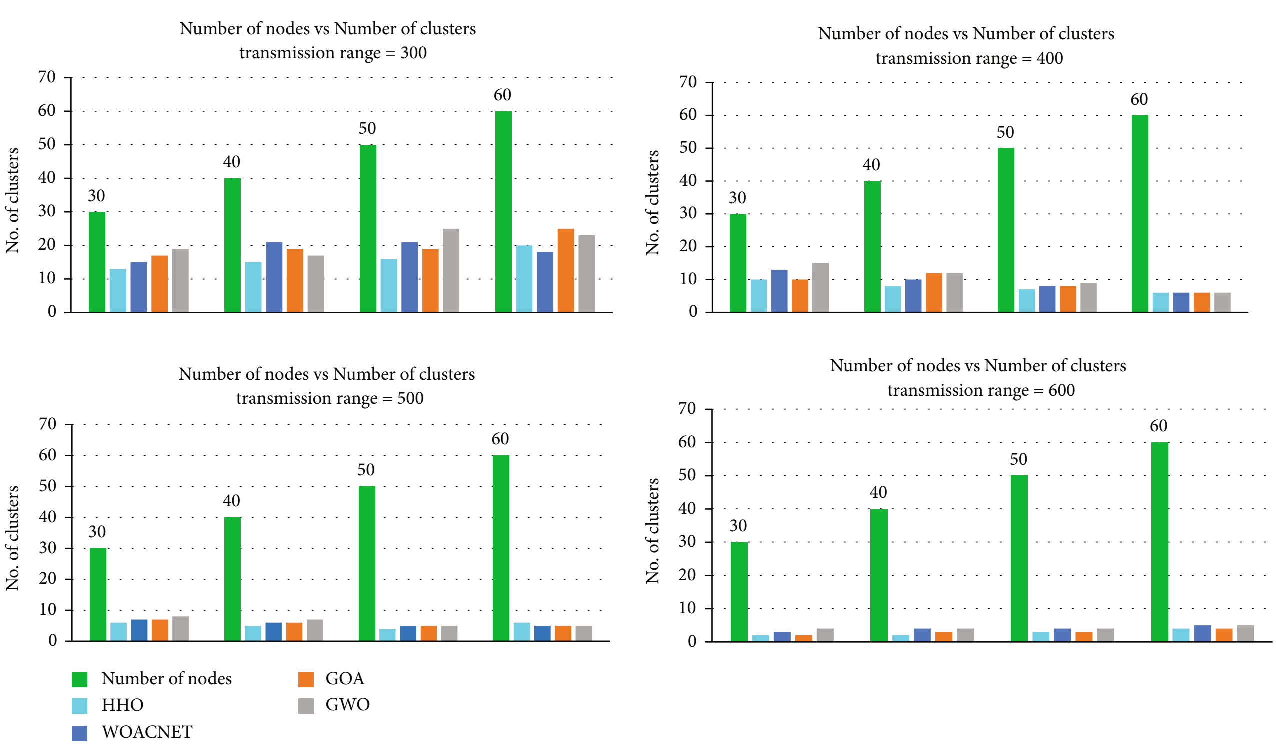

Figure 5: Number of nodes vs. CHs for transmission range 300 m-600 m and grid 1 km × 1 km.

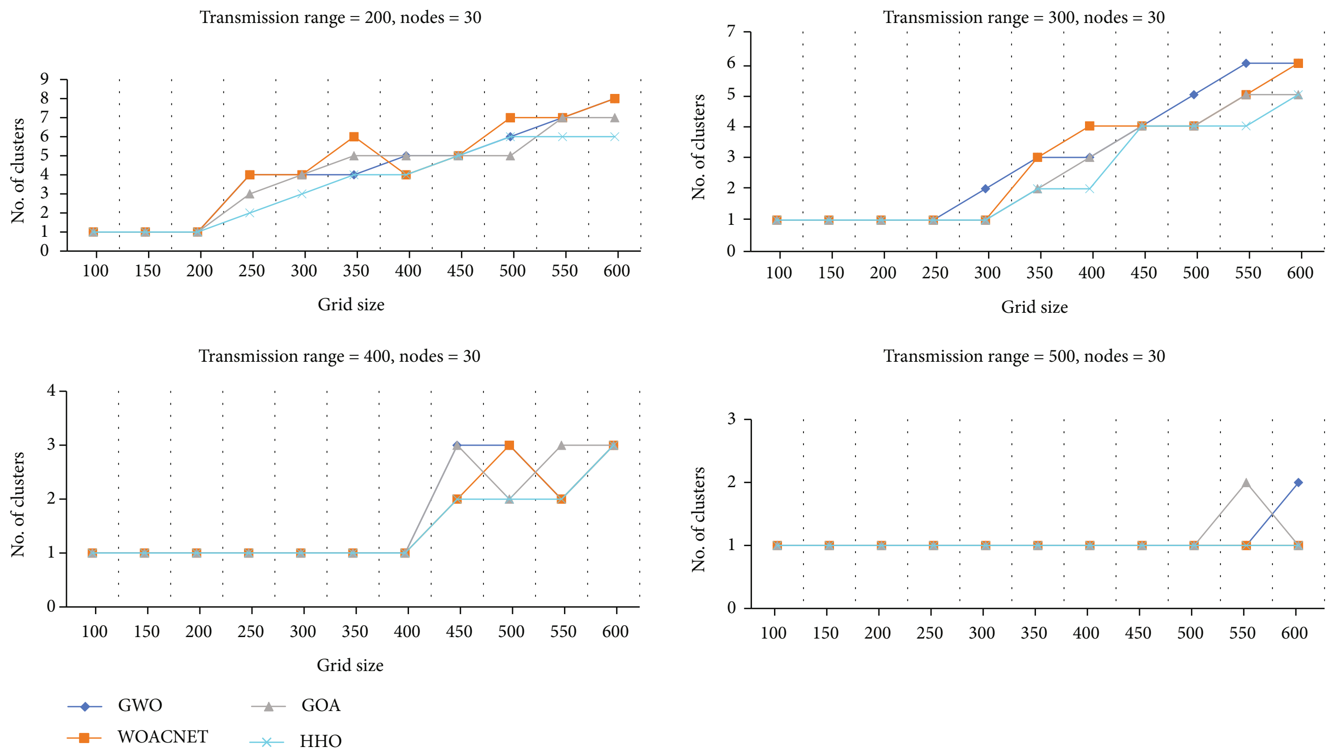

Figure 6: Network size vs. number of clusters for 30 nodes.

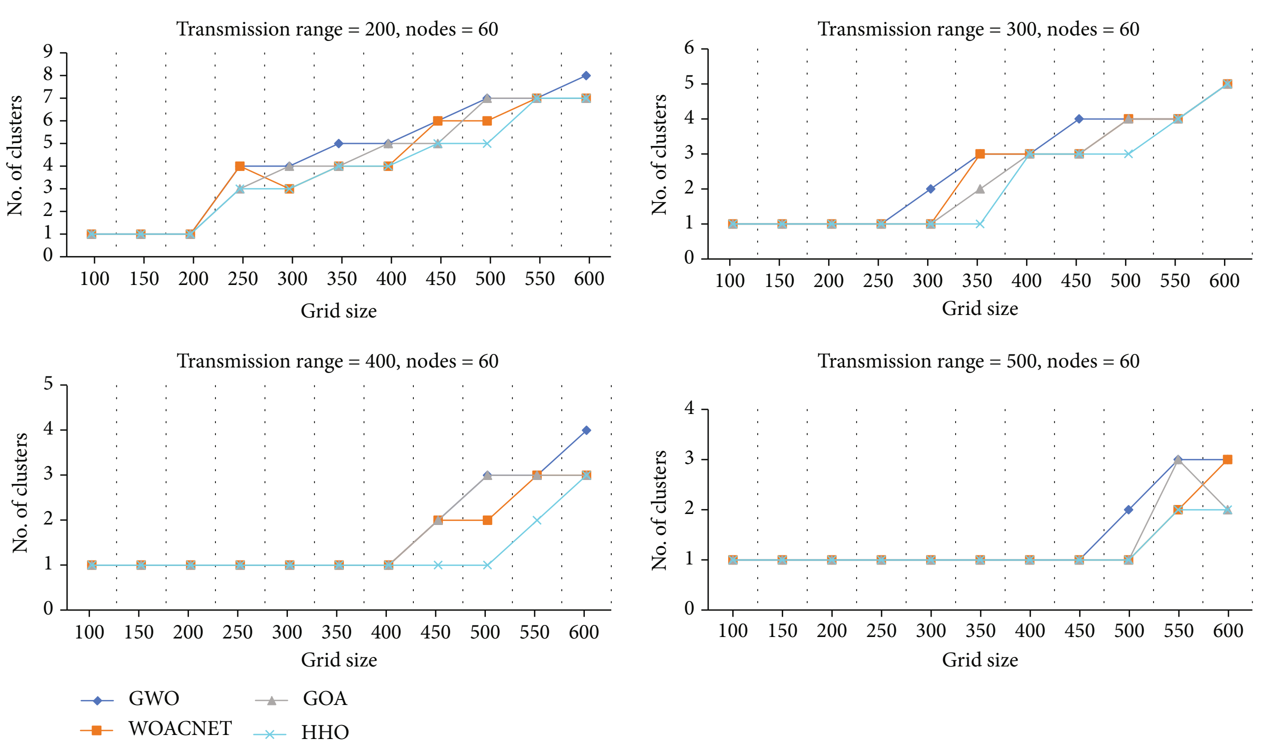

Figure 7: Network size vs. number of clusters for 60 nodes.

The findings are shown in figures 6 and 7 which were obtained by altering the communication range from 200 m to 500 m while taking into account 30 and 60 nodes and dynamic grid size. The results clearly show that iCHHO outperforms other well-known methods as cited in literature from [35–56].

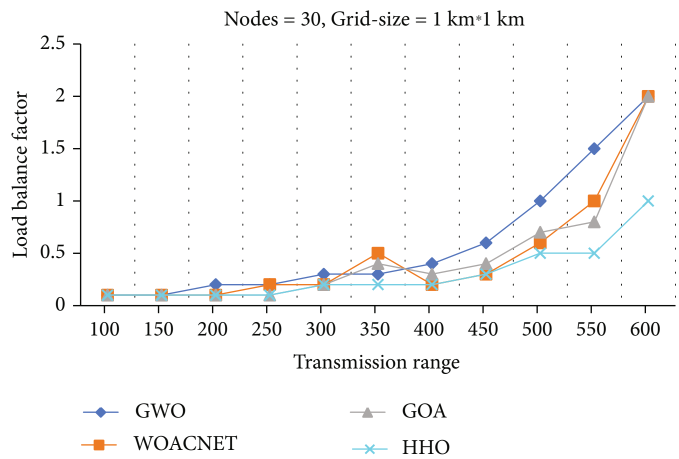

Figure 8: Load balance factor for 30 nodes at the grid size of 1 km × 1 km.

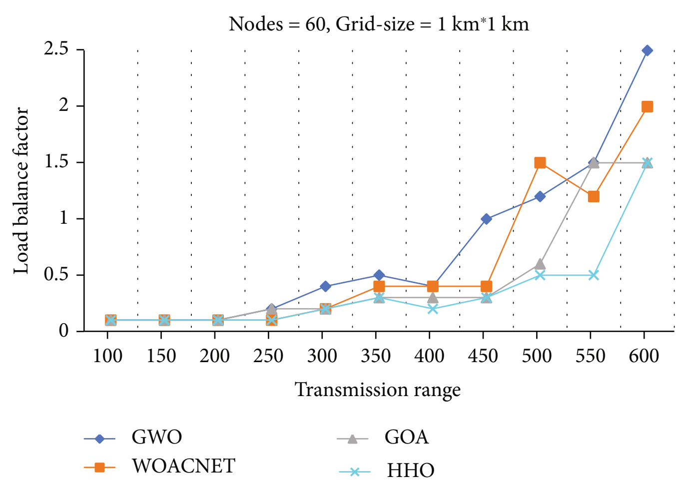

Figure 9: Load balance factor for 60 nodes at the grid size of 1 km × 1 km.

Table 2: Regression coefficients vs no. of clusters under Fully Modified Least Square (FMOLS) methods.

Dependent variables	Variable	Coefficient	Prob.	R-squared	Adjusted R-squared	ANOVA
NO_CLUSTERS_GWO [37]	TR	-0.042088	0.0097	0.775376	0.749798	$F(1, 9) = 40.18^{***}$
	C	27.73294	0.0005			
NO_CLUSTERS_GOA [36]	TR	-0.040038	0.0124	0.816213	0.794190	$F(1, 9) = 54.31^{***}$
	C	27.15528	0.0006			
NO_CLUSTERS_WOACNET [35]	TR	-0.040015	0.0095	0.879748	0.835216	$F(1, 9) = 67.85^{***}$
	C	27.34703	0.0004			
NO_CLUSTERS_iCHHO developed method	TR	-0.039256	0.0092	0.943748	0.912216	$F(1, 9) = 79.29^{***}$
	C	27.00485	0.0003			

TR: transmission range; C: no of clusters.

The load balancing factor is employed to validate the results by comparing them to an established method and evaluating the generated method against it. The number of vehicles (load) against each cluster head is efficiently and effectively balanced by iCHHO, which surpasses other benchmark algorithms in Figures 8 and 9.

5. Statistical Analysis for Evaluation

In this section, we perform various statistical tests, such as Fully Modified Least Square (FMOLS), which includes a p-test, regression analysis, and ANOVA to investigate the capabilities of the proposed method. Also, we compare the results with other state-of-the-art methods, as shown in Table 2.

In the cases of iCHHO, WOACNET, GWO, and GOA, Table 2 illustrates the effect of transmission range on the number of clusters. According to the theory, the smaller the communication range, the fewer clusters there will be. In the case of iCHHO, we found that increasing the transmission range by 1% reduces the number of clusters by.039%. In comparison, the change in TR for the other three state-of-the-art approaches, WOACNET, GWO, and GOA, is less than 0.040, 0.042, and 0.040, respectively. The R^2 value shows the predictor variable explained 0.94%, 0.87%, 0.77%, and 0.81% variance, respectively, in the outcome variable, i.e., no. of clusters with $F(1, 9) = 79.29^{***}$, $F(1, 9) = 67.85^{***}$, $F(1, 9) = 40.18^{***}$, and $F(1, 9) = 54.31^{***}$.

6. Conclusion

This paper proposed a novel clustering strategy for the optimization of resources. This study implements a nature-inspired clustering optimization technique that is influenced by Harris Hawks behavior. This method's performance is evaluated and analyzed using both modern and advanced approaches. In terms of the number of CHs, the developed method (iCHHO) outperforms the existing algorithms, such as GOA, WOACNET, and GWO (by 79%) when communication ranges, network size, and the number of vehicles are varied. Moreover, the proposed method lowers the network's overall costs by reducing the cluster heads to near-optimal levels and increasing cluster stability. Also, the routing scalability and reliability could be improved by deploying the proposed clustering in VANETs, as it groups vehicles thus forming a hierarchical network based on geographical and velocity distribution.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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