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Multi-Objective Harris Hawks Optimization Algorithm Based 2-Hop Routing Algorithm for CR-VANET

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ABSTRACT Vehicular Ad Hoc Network (VANET) emerges to ameliorate road accident, traffic congestion, and infotainment. Cognitive radio (CR) is integrated with VANET (termed as CR-VANET) to deal with the spectrum scarcity problems. For better data transmission, routing is very important in a highly dynamic CR-VANET environment. Routing in CR-VANET has several challenges due to vehicles' high-speed movements and channel accessibility issues. This paper proposes a 2-Hop routing algorithm based on the Multi-Objective Harris Hawks Optimization (2HMO-HHO) algorithm that chooses the optimal forwarders between the source and destination vehicles. Selecting 2-hops instead of multiple hops or the entire route increases the selected route's stability and assures successful data transmission. The simulations performed in OMNeT++ with SUMO show that the proposed algorithm achieves promising results on throughput, delay, packet delivery ratio, packet loss rate and communication overhead.

INDEX TERMS VANET, Routing algorithm, 2-hop routing, Harris Hawks Optimization, cognitive radio, throughput, packet delivery ratio, delay, packet loss rate, communication overhead.

I. INTRODUCTION

Because of the rapid population increase and the proliferation of automobiles, traffic jam and road safety create exasperating and complicated challenges in many metropolitan areas. About 1.25 million individuals worldwide die from road collisions every year [1]. On the other hand, traffic jam reasons costly delays, anxiety, noise, and unnecessary natural resources usage such as fuels. A smart and effective transport system, which increases economic productivity, can provide efficient road traffic, minimize accidents and an eco-friendly atmosphere. The vehicular ad hoc network (VANET) is emerged to enhance road safety and decrease traffic congestion. These provide improved safety and reduced travel time of commuters, especially in busy hours. However, the fast

development of wireless equipment creates the need for a large spectrum to facilitate high-volume data transfer.

The two VANET wireless access standards are dedicated short-range communication (DSRC) and wireless access in vehicle environments (WAVE). The Federal Communications Commission (FCC) has allocated 75 MHz bandwidth within the frequency range of 5.85–5.925 GHz to DSRC. DSRC is based on the IEEE802.11 (wireless local area networks) specification developed in 2003. Because of the vehicles' high speed and the complex shift in network topology, DSRC produces significant overhead and high latency. Therefore, DSRC is not suited for high-speed VANET. A new updated DSRC version, called WAVE, was introduced to make it adaptable, suitable and consists of two protocol suits, IEEE802.11p and IEEE 1609 [2]. DSRC's dedicated 75 MHz for VANET is insufficient to handle VANET's gigantic data transfer [1]. That means spectrum shortage (inadequate allocation relative to demand) has impeded VANET

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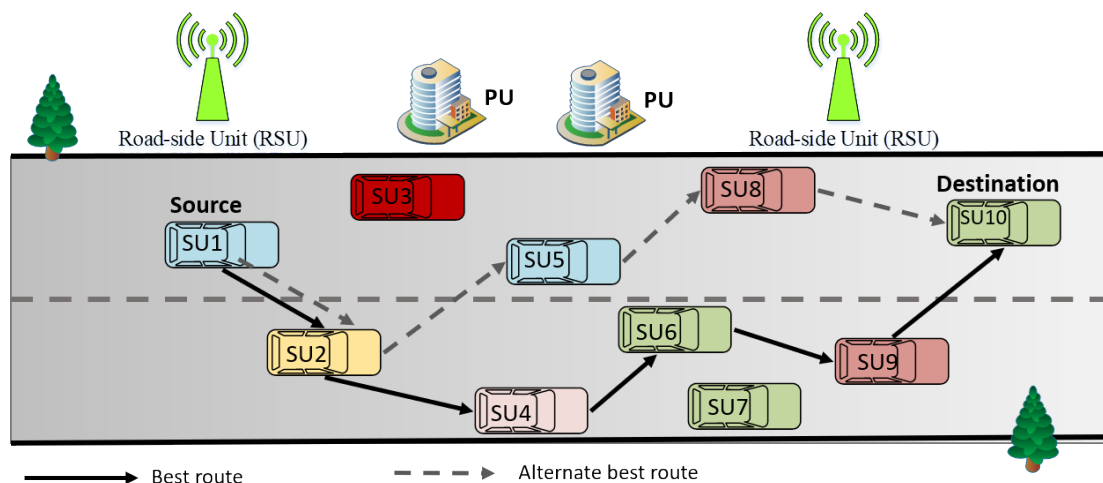


FIGURE 1. Routing in CR-VANET.

implementation. There are other access standards or V2X (vehicle to everything) protocols for VANETs are Wi-Fi [3], LTE-V [4], Visible light communication (VLC) [5], 5G (Cellular-V2X or C-V2X) [6], Millimeter wave (mmWave) communications [7], Bluetooth [8], etc. These access standards can be used as an alternative solution of DSRC when overcrowding occurs (i.e., excess bandwidth is needed for massive data communication, and DSRC alone is insufficient to handle). The cognitive radio (CR) technique is used to switch between the access techniques when is DSRC is fully occupied.

CR, implemented by Mitola textitet al. [9], is a key spectrum sharing technology that enables wireless nodes to dynamically sense and utilize underused licensed channels (for example, television channels) in an adaptable way. It also allows users to vacate licensed channels when it is re-occupied by licensed users. In resolving VANET's spectrum scarcity problem, CR may play a crucial role [10]. Therefore, CR-based VANET or CR-VANET is a promising technology for addressing road safety, traffic jam, and entertainment issues. It can serve as a fundamental building block for the next generation's transport systems, particularly autonomous driving vehicles.

Routing for VANET is applied to select the best route between the sending vehicle and the receiving vehicle via a set of other elements of VANET (e.g., other vehicles, roadside units (RSU)). The communication must ensure the best quality of service (QoS), including the least delay, higher throughput, etc. In specific, to exchange vehicle safety messages, such routing is required in which the overall delay must be shorter than the predefined value. Also, the reliability of the communication must be high. In short, to facilitate successful data transfer, optimum route selection matters [11].

As the mobility of vehicles is high, the VANET is often modified quickly. This frequent change of topology reasons a delay in message transmission and also data loss. The basic routing protocol cannot deal well with the dynamics of VANETs. Hence, stable and intelligent routing protocols

are required [12]. CR-VANET routing depends heavily on the whole CR loop and primary users (PUs) activities. QoS metrics, channel bandwidth, throughput, latency also influence this routing. If PU activity, for example, is low, the topology of secondary users (SUs) is comparatively static. Vehicles in CR-VANET are the SUs.

Conversely, the abrupt emergence or re-appearance of PUs creates unintended path loss. Instant alternate-routing is essential for smooth communication. That is why CR-VANET routing should be versatile and adaptable [10]. Figure 1 illustrates CR-VANET's routing situation.

For example, the source vehicle (SU1) selects a route SU1-SU2-SU4-SU6-SU9-SU10 as the best route using a routing algorithm. This is because the route has high bandwidth and reliability, low latency, and low PU activity. While there are a limited number of hops with high throughput on the route SU1-SU3-SU8-SU10, this route would be avoided as the route is vulnerable to PU involvement.

On the other hand, because of high-speed mobility, SU4 could be beyond the range of SU2. Therefore, the best route mentioned above might fail. In this situation, the best alternative route for seamless communication would be selected immediately. For example, the SU1-SU2-SU5-SU8-SU10 route may be the best alternate route. In short, the routing of CR-VANET differs from the conventional routing of VANET or CR, and this is not very easy to handle.

In routing, it is critical to select the entire route in VANET as the vehicle moves faster. If the vehicles move far along the route, frequent route selection is required, and hence retransmission increases. Although the forwarder is selected, channel and vehicle features need to be considered.

This paper proposes a 2-hop routing algorithm. Here, the route is selected by considering multiple objectives: direction, mobility, vehicle state, channel availability. The computation of significant vehicle-based characteristics leads to choosing an optimal route. The source transmits the data to the sequentially selected 2-hop neighbors towards the destination. Here, the nearest 1-hop neighbors will receive the

source node packet and hence the packet loss is mitigated. The proposed 2-Hop Multi-Objective Harris Hawks Optimization (2HMO-HHO) algorithm is constructed upon the Harris Hawks Optimization (HHO) algorithm, which is a new bio-inspired algorithm that comprises the cooperative hunting behavior of Harris Hawks [13]. It is found better than the conventional algorithms in optimization problems [13]. Thus, we have formulated our 2-hop forwarder selection as an optimization problem and resolved it using the 2HMO-HHO algorithm.

The rest of the paper is structured as follows: Major research works carried out on CR-VANET routing are studied in Section II. The proposed algorithm is detailed in Section III. Section IV discusses the simulation setup, while section V analyses the results with the comparative analysis. Finally, the paper is concluded in section VI.

II. RELATED WORKS

This section reviews the current research works and summarizes the research gap that needs to be focused on improving routing efficiency in CR-VANET.

The authors in [14] proposed a routing, message scheduling scheme and buffer management policy. For scheduling, an optimized binary tree replication algorithm is introduced. In routing, the forwarding set is selected by determining the channel availability and transmission range. Then the vehicles with a high priority will transmit the data first from the forwarding set. The vehicle at the farthest hop distance is given higher priority. Each message from the nodes is assigned with tags as fast-forward and reliable forward. Based on these tags, buffer management is performed by deleting the arrived message. For optimal route selection, spectrum availability is considered a significant metric. Here, the Markov model's channel availability detection is inaccurate due to inappropriate detection and the lack of adaptability to the signals' covariance, which leads to non-optimal forwarder selection. Here, the priority of vehicles is defined based on their hop count. Still, in vehicular communication, the nodes at 1-hop could also have higher mobility which may leave the route, then occurs packet loss. Here the 1-hop and 2-hop nodes will have lesser priority than the farthest vehicle.

In [15], the authors proposed a modified cognitive tree routing protocol (MCTRP) that combines a genetic whale optimization algorithm (GWOA). In the proposed MCTRP handles three steps as (i) route discovery are performed and then (ii) channel is selected for the route, and (iii) data transmission. The node with maximum node identity and a sequence number is chosen as a root node. Once the root node advertises, it joins all the child nodes and forms a tree. Using GWOA, an optimal root is selected by estimating the cost, the node with minimum cost is chosen for transmission. In GWOA, crossover and mutation operation are performed to update the position. In route selection, the objective function is used to select a route with a minimum cost; here, it does not consider channel capacity and other significant constraints, so the route chosen is inefficient. The use of

hybrid optimization consumes time to select a transmission route due to the operators used in a genetic algorithm. Also, selecting a complete route leads to higher packet loss since the vehicles move faster, but those vehicle characteristics were not considered. Also, the vehicular nodes are dynamic, so the construction and maintenance of vehicles' tree-based structure are tedious.

Self-decision vehicle control with cognitive framework stores routes in the memory is proposed in [16]. For the maintenance of routes in the memory, it uses a fuzzy model in the system. The inputs are route, route profile, infrastructure information, error probability, previous behavior, uncertainty, protocol, etc. Based on the fuzzy rule, the desired route information is obtained. Route storage and maintenance in each vehicle increase overhead and complexity. Fuzzy-rule based optimal relay selection is enabled among vehicles [17]. Here, an evaluation index set is computed from the absolute values of speed, driving direction, hop count and connection time. The degree of satisfaction is determined, and the index weight vector is computed from the analytical hierarchy process (AHP). As a result, an optimal forwarder is selected from this process for data transmission. Execution of fuzzy and AHP sequentially for each relay selection increases time consumption.

The relay selection method estimates message delivery time between source and destination [18]. Once the vehicle receives a response, it then checks the idle channel, and if a channel is not available, it performs the store-carry and forward method. If the channel is inactive, it computes the message delivery time and transmits the packet to the destination. Here, store-carry and forward are subjected to higher delay due to switching in this method. The delay in increased data forwarding is not suitable for a high dynamic vehicle network. For video streaming, routing is enabled by taking into account two main constraints: link efficiency and quality of experience (QoE) [19]. The reinforcement learning of Q-learning is used to validate the predicted distance, and then it selects the next forwarder. This work collects vehicle information as mean opinion score, position, direction, link quality, link lifetime, density, and buffer-level. The Q-value in the reinforcement learning updates this value in the Table. Generally, the Q-learning approach can learn a single environment by a single agent, which is insufficient for large-scale networks.

An improved distance-based ant colony optimization routing (IDBACOR) is introduced in a VANET environment [20]. The modified ant colony optimization (ACO) algorithm performs the following steps: pheromone deposit, pheromone update, probabilistic model, decision-making, and data transfer. On the performance of these steps, it selects an optimal shortest path. Distance is one of the key metrics that is considered for route selection. It also includes location, velocity, and propagation delay in the vehicle's node for route selection. The ACO algorithm is not aware of convergence, and hence it takes time to select a route between source and destination.

The authors in [21] formulated the data offloading problem as an optimization problem considering the delay

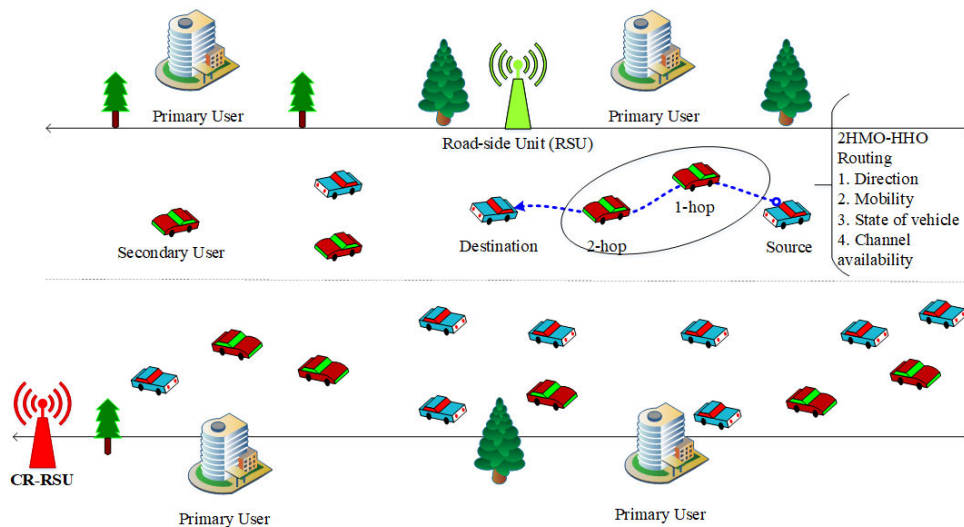


FIGURE 2. System model.

constraint of different applications. The optimization problem is modeled as a nonlinear integer programming problem. Two low-complexity methods: The Greedy Winner Selection Method (GWSM) and the Dynamic Programming Winner Selection Method (DPWSM), were proposed to solve the problem.

Cao *et al.* in [22] examined the viability of using the nature of delay/disruptive tolerant networking (DTN) in VANET’s opportunistic vehicle to vehicle (V2V) communications. This is because of its flexibility and cost-efficiency in VANETs. According to the authors, the store-carry-forward (SCF) mechanism in DTNs makes routing feasible in VANETs as it must deal with the frequent intermittent connectivity due to the high mobility of the vehicles. For DTN routing, the encounter prediction is important when the utility metric is defined differently to determine whether a node found is a good relay. They proposed Electric vehicles’ charging station selection scheme to minimize the charging waiting time.

A social-aware routing scheme is presented in cognitive radio vehicular ad hoc networks [23]. The SUs are categorized into intra-community and inter-community. A graph is constructed for PUs, since their locations are static in the network; it measured node centrality from the graph. Further, the shortest path is selected based on the hop count. This work also proposes an optimized binary tree as a replication policy to mitigate copies of the same packet. The selection of route using minimum hop counts fails to assure the route’s stability since the intermediate hop can also have higher mobility and moving in the opposite direction.

This paper proposes a CR-VANET routing algorithm that can perform routing without any breakage and improve the delivery ratio and other QoS parameters. Unlike end-to-end route selection (since it is affected by vehicle speed and direction that leads to high data loss), we presented a novel 2-hop route selection methodology. The proposed 2-hop routing selects optimal 2-hop forwarders by the 2HMO-HHO algorithm.

III. PROPOSED ROUTING ALGORITHM

In this section, we explain the proposed work in detail with the proposed algorithm.

Figure 2 shows the system model of our proposed algorithm. The proposed CR-VANET model comprises of N number of vehicles as v_1, v_2, \dots, v_N . From here, SUs and vehicles represent the same since the vehicles are the SUs in our work. The SUs sense the licensed spectrum of PUs if DSRC is fully occupied. The network model also consists of RSUs or CR based RSU (CR-RSU). RSU is responsible for allocating the vacant spectrum to the SUs. Here, we have considered the road as a single segment.

SU does the spectrum sensing (finding out the presence or absence of any PU) [24]. At the same time, segment management and channel allocation management are carried by RSUs. Finally, on the assigned channel, data is transmitted through optimal 2-hop neighbors.

Once the vehicle has a channel (after CR processes) for data transmission, the next step is to perform 2-hop routing. In this work, we have focused on optimal 2-hop forwarder selection rather than entire path selection. The selected entire path can be affected by several environmental factors such as vehicle speed and direction, channel availability etc. Thus, we have intended to perform optimal 2-hop forwarder selection. For this purpose, we proposed a novel 2HMO-HHO algorithm. HHO is a nature-inspired population-based metaheuristic algorithm. It mimics the cooperative hunting behavior of Harris Hawks for the preys like rabbits.

Figure 3 shows the proposed concept of the proposed routing in CR-VANET. Here, the optimal 2-hop forwarders are selected for data transmission. After 2-hop forwarders selection, the data is transmitted up to 2-hops, and the 2nd hop forwarder again selects optimal 2-hops forwarders until the data reaches destination. The involvement of 2-hop routing improves data transmission.

Table 1 includes the notations and their definitions used in our 2HMO-HHO algorithm.

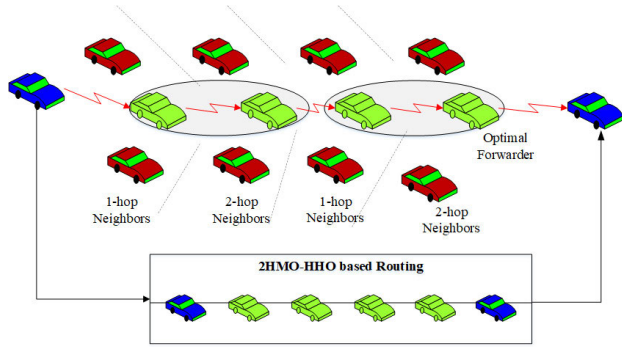


FIGURE 3. Proposed 2-hop routing.

TABLE 1. Notation and their definitions.

Notation	Definition
$f(v_i)$	fitness function of i^{th} vehicle
N	number of population
\mathbb{D}	direction of the vehicle
\mathbb{M}	mobility of the vehicle
\mathbb{S}	state of the vehicle
\mathbb{C}	spectrum or channel availability
DR	data rate
r	location vectors of the hawks
η	random number of the range of [0,1]
\mathcal{E}_0	initial energy of the prey
\mathcal{E}_{prey}	energy of the prey after certain time
\mathbb{C}	next moving step
\mathbb{B}	random vector
$LF(d)$	levy flight with the dimension d
U	Current iteration
U_m	maximum number of iteration

The proposed 2HMO-HHO algorithm involves the following steps,

a) Initialization Phase –

This phase initializes all solutions as the initial hawks' populations. Here, the population comprises the multiple (N number of) neighboring vehicles (v_1, v_2, \dots, v_N). Here, N is the number of populations. The algorithm is executed by the source vehicle (v_{so}). Here, the source vehicle and the neighboring vehicles are considered 'hawks', and the destination vehicle is considered prey (rabbit). In this phase, the fitness function is computed for all vehicles. For instance, the fitness of i^{th} vehicle ($f(v_i)$) is computed as follows,

$$f(v_i) = \left\{ \sum \mathbb{D}, \mathbb{M}, \mathbb{S}, \mathbb{C} \right\} \quad (1)$$

The fitness is formulated as the function of direction (\mathbb{D}), mobility (\mathbb{M}), state of the vehicle (\mathbb{S}), and spectrum or channel availability (\mathbb{C}). Here, the vehicle's direction is represented

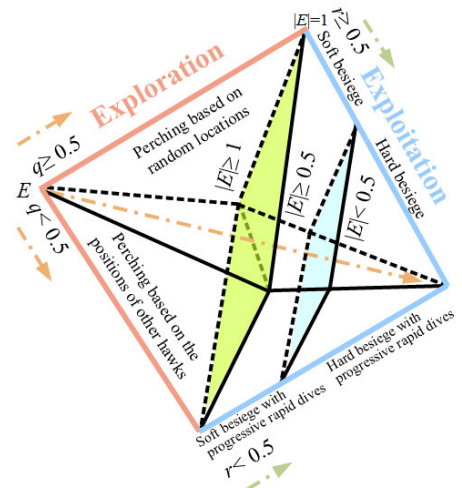


FIGURE 4. Different phases of HHO [13].

as binary values [0] and [1]. If the direction of the candidate vehicle and destination vehicle is the same, then $\mathbb{D} = 1$. Otherwise, it is 0. If the destination and candidate vehicles are in the same direction, the vehicle's fitness will increase. Similarly, the mobility value is also mapped to [0] and [1] to enrich the fitness computation method. If the mobility of v_i is higher than the average mobility of the segment, then $\mathbb{M} = 0$ else $\mathbb{M} = 1$. If v_i has the available channel (either DSRC or CR channel) for the data transmission, then $\mathbb{C} = 1$, otherwise $\mathbb{C} = 0$. In contrast, \mathbb{S} is formulated as the function of multiple metrics as follows,

$$\mathbb{S} = \frac{T + DR}{D} \quad (2)$$

For v_i , \mathbb{S} is the function of throughput of the v_i (T), data rate of v_i (DR) and delay (D). The \mathbb{S} is the deciding factor of fitness computation since the effective channel utilization can only be achieved using an optimal path for data transmission. In this way, the $f(v_i)$ is computed for all vehicles in the population.

The HHO algorithm includes phases of exploration, transformation, and exploitation, like other meta-heuristic algorithms. The Hawks will be found randomly at different locations during the exploration phase to observe and catch the rabbit. The hawks take surprise pounce or teams of rapid dives to exploit the expected presence neighborhood at the exploitation phase. Hawks' positions are regarded as candidate solutions. The best position is the expected position for the rabbit. Figure 4 shows those different phases of HHO. The details of these phases are described below:

b) Exploration phase –

This phase executes the process of wait, search, and detection of prey. The position of a hawk is represented as follows,

$$v_i(U + 1) = \begin{cases} v_{i_{rand}}(U) - r_1 |v_{i_{rand}}(U) - 2r_2 v_i(U)| & \text{if } r \geq 0.5 \\ v_{i_p}(U) - v_{i_a}(U) - r_3(l_b + r_4) & \text{if } r < 0.5 \end{cases} \quad (3)$$

Here, U represents the current iteration, and $U + 1$ represents the next iteration. Besides, r_1, r_2, r_3 and r_4 represent the location vectors of the hawks, while y is the random number selected in the range of $[0,1]$. The average location of the hawks (v_{i_a}) is formulated as,

$$v_{i_a}(U) = \frac{1}{N} \sum_{j=1}^N v_j(U) \quad (4)$$

c) Transformation Phase –

This phase transfers from the exploration phase to the exploitation phase. The energy of prey is decayed during evading behavior. It can be estimated as,

$$\varepsilon_{Prey} = 2\varepsilon_0 \left(1 - \frac{U}{U_{max}}\right) \quad (5)$$

Here, ε_0 is the initial energy state of the prey, U is the number of the current iteration and U_m is the maximum number of iterations.

D) Exploitation Phase –

In this phase, the hawks attack the selected prey estimated in the previous phase. In this phase, four different strategies have been utilized, such as soft besiege, hard besiege, soft besiege with progressive rapid dives, and hard besiege with progressive rapid dives. The occurrence of soft and hard besiege relies on energy level (i.e.) $|\varepsilon_{prey}| \geq 0.5$ and $|\varepsilon_{prey}| < 0.5$.

Soft Besiege:

If $r \geq 0.5$ and $|\varepsilon_{prey}| \geq 0.5$, then soft besiege strategy has been selected. It can be modeled as follows,

$$v_i(U+1) = \Delta v_i(U) - \varepsilon_{prey} |\mathfrak{B} v_i(U) - v_i(U)| \quad (6)$$

where \mathfrak{B} us the jump intensity of evading process that can be represented as $\mathfrak{B} = 2(1 - r_5)$ and $\Delta v_i(U) = v_{prey}(U) - v_i(U)$.

Hard Besiege:

$r \geq 0.5$ and $|\varepsilon_{prey}| < 0.5$, then soft besiege strategy has been selected. It can be modeled as follows,

$$v_i(U+1) = v_{prey}(U) - \varepsilon_{prey} |\Delta v_i(U)| \quad (7)$$

Soft Besiege with Progressive Rapid Dives:

If $r < 0.5$ and $|\varepsilon_{prey}| \geq 0.5$, then soft besiege strategy has been selected. It can be modeled as follows,

$$\mathfrak{S} = v_i(M) - \varepsilon_{prey} |\mathfrak{B} v_{prey}(U) - v_i(U)| \quad (8)$$

The above model computes the next moving step (\mathfrak{S}) of the hawks. Also, the hawks dive to attack the prey based on the following equation,

$$Di = \mathfrak{S} + B * LF(d) \quad (9)$$

Here, \mathfrak{B} is the random vector and $LF(d)$ is the levy flight with the dimension d . In this phase, the location is updated as,

$$v_i(U+1) = \begin{cases} \mathfrak{S} & \text{if } f(\mathfrak{S}) < f(v_i(U)) \\ Di & \text{if } f(Di) < f(v_i(U)) \end{cases} \quad (10)$$

Hard Besiege with Progressive Rapid Dives:

Algorithm 1 2HMO-HHO Routing Algorithm

Inputs: The population size N and maximum number of iterations U_m

Outputs: The location of the rabbit and fitness value

Begin

Initialize Population v_1, v_2, \dots, v_N

while ($(U \leq U_m)$) **do**

For all $v_i \in N$

 Compute $f(v_i)$ % here, consider the fitness values of hawks%

 Setting $v_{prey}(U)$ as the best location of the rabbit

for (each hawk v_i) **do**

 Update

 initial energy $\varepsilon_i = 2rand()$

 Jump strength, $J = 2(1 - rand())$

 Estimate ε_{Prey} using Eq. (5)

if ($|\varepsilon_{prey}| \geq 1$) **then** %Exploration phase%

 Update $v_i(U+1)$ by Eq. (3)

if ($|\varepsilon_{prey}| < 1$) **then** %Exploitation phase%

if ($|\varepsilon_{prey}| \geq 0.5 \ \&\& \ r \geq 0.5$) **then** % Soft besiege%

 Update $v_i(U+1)$ by Eq. (6)

else if ($|\varepsilon_{prey}| < 0.5 \ \&\& \ r \geq 0.5$) **then** %

 Hard besiege%

 Update $v_i(U+1)$ by Eq. (7)

else if ($|\varepsilon_{prey}| \geq 0.5 \ \&\& \ r < 0.5$) **then** %

 Soft besiege with progressive rapid dives%

 Update $v_i(U+1)$ by

 Eq. (10)

else if ($|\varepsilon_{prey}| < 0.5 \ \&\& \ r < 0.5$) **then** %

 Hard besiege with progressive rapid dives%

 Update $v_i(U+1)$ by

 Eq. (11)

Return the best location of v_{prey} % global optimal solution or 2_hop_forwarders%

End

If $r < 0.5$ and $|\varepsilon_{prey}| < 0.5$, then soft besiege strategy has been selected. Here, the location is updated as follows,

$$v_i(U+1) = \begin{cases} \mathfrak{S} & \text{if } f(\mathfrak{S}) < f(v_i(U)) \\ Di & \text{if } f(Di) < f(v_i(U)) \end{cases} \quad (11)$$

From here, \mathfrak{S} is estimated by the following equation,

$$\mathfrak{S} = x_{prey}(U) - \varepsilon_{prey} |\mathfrak{B} v_{prey}(U) - v_{i_a}(U)| \quad (12)$$

Based on the above rules, the 2HMO-HHO algorithm updates the preys' location in the population based on a fitness function. Over a given iteration, the optimal solution is returned from the 2HMO-HHO algorithm. In this work, the optimal solution denotes optimal 2-hop forwarders from the source node towards the destination.

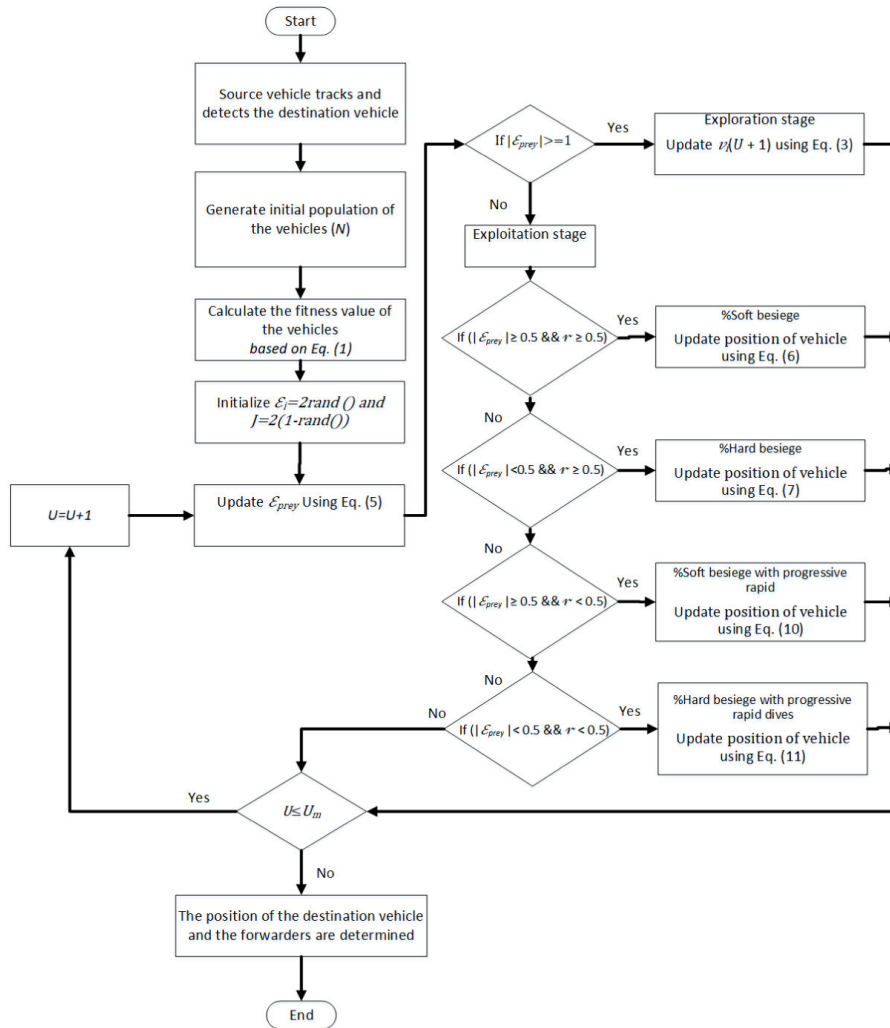


FIGURE 5. Flowchart of proposed 2HMO-HHO routing algorithm.

Algorithm 1 shows the proposed 2HMO-HHO routing algorithm.

Figure 5 shows the flowchart of the proposed 2HMO-HHO routing algorithm for CR-VANET. Here, the Harris Hawks are aligned with the source vehicles and the forwarding vehicles and the rabbit (the prey) is aligned with the destination vehicle.

IV. SIMULATION SETUP

This section first discusses the simulation’s parameter setting and later discusses the real-life simulation application scenario.

A. PARAMETERS SETTINGS

To evaluate the proposed algorithm, we designed our proposed vehicle network using a network simulation tool, namely OMNeT++ [25] with the SUMO framework[26]. OMNeT++ is a C++ oriented simulation platform that facilitates the efficient simulation of vehicle-based networks and many other network protocols. We have used the

Veins [27], INET [28], and CrSimulator frameworks [29] on the OMNeT++ platform. The type of mobility of vehicles is considered based on the Veins’ submodule TraCIMobility. Rayleigh multipath propagation model is considered in this work. The channel vector is modeled as a zero-mean and complex random Gaussian vector. Some physical layer characteristics, such as shadowing, Doppler fast fading effects, etc., have been skipped for simplicity. Detailed simulation parameters are shown in Table 2.

We first create a CR-VANET environment with the above configuration. Then, we perform data transmission to test the proposed work performance. To measure the performance, we then implement spectrum sensing, decision making and route selection processes on the created environment. The performance is measured in terms of performance metrics.

B. APPLICATION SCENARIO

We have tested our proposed work on the internet of vehicles (IoV) environment. In IoV, the vehicle mainly relies on sharing safety information such as parking slot availability,

TABLE 2. Simulation settings.

Parameter	Value /Range
Simulation Area	2750 m× 2250 m
Number of vehicles	100
Number of PUs	10
Number of RSUs	2
Vehicle speed	0-30 m/s
Vehicle acceleration	2.5 m/s ²
Data rate	18 Mbps
Number of packets	10000 (approx.)
SNR	-10dB
MAC header length	256 Bit
Data Packet Size	512 Kbyte
Packet Interval	0.1s
Data Rate	up to 18Mbps
Sensing duration	6ms (Maximum)
Transmission duration	12ms (Maximum)
Delay	0~18 ms
Number of DSRC (dedicated short-range communication) channels	6
DSRC bandwidth	10 MHz
TV channels bandwidth	6 MHz (500MHz – 524MHz)
Number of TV channels	4
Simulation time	500 seconds

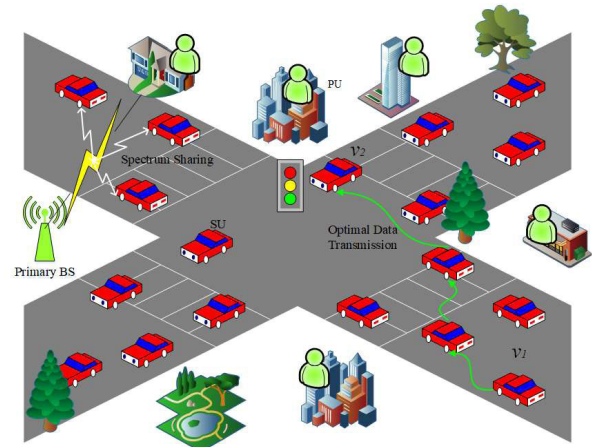
accident warning, traffic density etc. and entertainment information such as video, multimedia files etc. Involvement of large file sharing and safety information sharing demands huge bandwidth. Thus, the integration of CR-VANET assists in provisioning IoV applications.

In Figure 6, the application scenario of the proposed routing algorithm is illustrated for IoV applications. Here, vehicle v_1 needs to transmit a video to v_2 . For that, it first performs spectrum sensing based on the current network situation. If the spectrum is found available, RSU assigns the available channel to the v_1 . At last, the video is transmitted to v_2 through optimal 2-hop neighbors. Here, we have illustrated an application for video transmission. Similarly, the proposed work is applicable for any kind of data or file sharing among intelligent vehicles in the IoV.

Here, PUs are considered static, and they follow a simple ON/OFF PU activity [24]. SUs are equipped with two antennas, one for DSRC and another for CR usage. Then, we perform data transmission to test the proposed work performance.

V. RESULTS AND DISCUSSIONS

This section provides a comparative analysis with the previous works. The section also discusses the results obtained from the simulation with the comparison of the previous works.

**FIGURE 6.** Application of scenario of Seg-CR-VANET in IoV.

A. COMPARATIVE ANALYSIS

This sub-section evaluates the proposed work with existing works to prove our proposed approach's efficacy. We compared our work with existing works such as Markov routing [14] and GWOA-GA [15]. These two algorithms have been discussed in detail in section II.

In [14], they used an optimized binary tree replication algorithm. The route is selected based on the channel availability and transmission range. They set the priority of vehicles based on their hop count. We have chosen this algorithm for comparison to show that selecting 2-hops is better than selecting the entire route. Moreover, according to their algorithm, the vehicle at the farthest hop distance is given higher priority. That means the 1-hop and 2-hop nodes will have lesser priority than the farthest vehicle. This phenomenon is the opposite of our proposed algorithm. Therefore, this is another reason to choose this algorithm for comparison.

We have used the bio-inspired optimization algorithm (i.e. HHO algorithm), while [15] also used a bio-inspired optimization algorithm (i.e. GWOA). We have chosen this latest work to compare with our work as they are in the same category. However, they used two algorithms (tree-based routing algorithm and genetic whale optimization algorithm) instead of using a single algorithm. We have used a single algorithm and found better results. This is another reason (using a single algorithm is better than using multiple algorithms) to choose [15] for the comparison.

A detailed comparison of the existing works is presented in Table 3.

The theoretical comparison shows that each existing work has some limitations and drawback. In contrast, the proposed 2HMO-HHO algorithm focuses on the improvement of the overall network performance. It can be tested through brief performance measures as in the following sub-sections.

B. PERFORMANCE ANALYSIS

1) ANALYSIS OF THROUGHPUT

Throughput is defined as the amount of data transmitted over the network over the given time slot. In the case of

TABLE 3. Comparison on existing works.

Previous Work	Research Purpose	Routing	Problems
Markov Routing [14]	To achieve data routing	Channel availability-based routing	<ul style="list-style-type: none"> In routing, forwarder is determined by validating the CR channel availability, but the presence of spectrum is predicted using hidden hyper parameters and the state transition using Markov model. The use of Markov model is not able to adapt covariance of the signals and hence CR channel detection is not accurate. The vehicle at farthest hop distance is given higher priority.
GWOA-GA [15]	To enable energy efficient routing	GWOA-GA	<ul style="list-style-type: none"> The use of hybrid optimization consumes time to select a route for transmission due to the operators used in genetic algorithm. Also, the selection of a complete route leads to higher packet loss, since here the vehicles move faster but those vehicle characteristics were not taken in account. The node with maximum identity and sequence number is selected as root node, but the identity of nodes is unique and fixed, hence the same node will have higher chances to be selected as root node. Also, the vehicular nodes are dynamic in nature, so the construction and maintenance of tree-based structure of vehicles is tedious. It does not consider channel capacity and other significant constraints, so the route selected is not efficient.

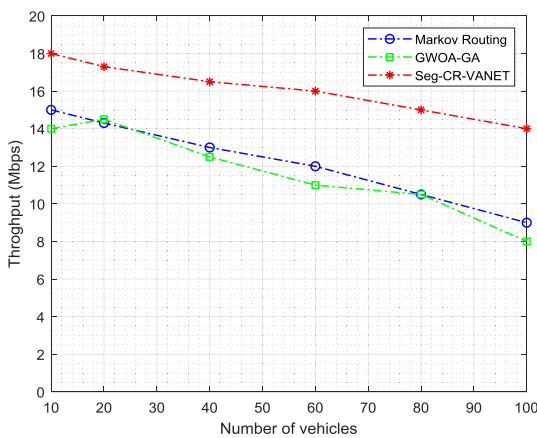


FIGURE 7. Throughput analysis.

CR-VANET, it much depends upon the channel availability and the proper routing.

In Figure 7, throughput comparison is shown concerning the number of vehicles. The analysis shows that all works decrease the throughput with an increase in the number of vehicles. Throughput is decreased as the number of vehicles are increased. This is because when more vehicles are in the VANET, it needs to sense for the spectrum hole as DSRC’s dedicated spectrum is exhausted. It needs to sense for the free or vacant spectrum. For the spectrum sensing purpose, the vehicle gives lesser time for data transmission. In other words, as the time slot is fixed, if a vehicle spends more time on spectrum sensing, it can get less time for the data transmission; as a result, the throughput is decreased. The time needed for the spectrum sensing influences the secondary network’s channel bandwidth throughput. Long sensing time

provides an effective sensing result. However, this comes at the expense of the throughput when more time is spent on sensing and less time is left for data transmission to the required channel for a given frame. A time slot or a frame consists of spectrum sensing and data transmission.

On the other hand, here, throughput is not decreased dramatically. This because a vehicle gets more forwarders to forward its data. In general, more vehicle in the network increases the throughput, but due to the shortages of the spectrum, and it must go for the spectrum sensing, the expected throughput is not achieved.

Our work maintains a better throughput, which is relatively greater than prior works. When the number of vehicles is 10, it achieves the maximum throughput of 18 Mbps. With the vehicle’s increase, the throughput falls to 14 Mbps (when the number of vehicles is 100). Simultaneously, Markov routing drops from 15 Mbps to 9 Mbps and GWOA-GA from 14 Mbps to 8 Mbps. This achievement’s primary reason is that the proposed work considered several significant parameters such as vehicle direction and speed, an average speed of the segment, average delay, data rate etc. Selecting 2-hop instead of the whole route provides stable routing. For these reasons, we have obtained good throughput compared to the previous works.

2) ANALYSIS OF PACKET DELIVERY RATIO

Packet delivery ratio (PDR) is defined as the ratio between the total number of packets generated to the number of packets successfully transmitted to the destination. In Figure 8, PDR is compared with a varying number of vehicles.

The PDR is decreased with a varying number of vehicles. This is due to contention in the wireless channel as the

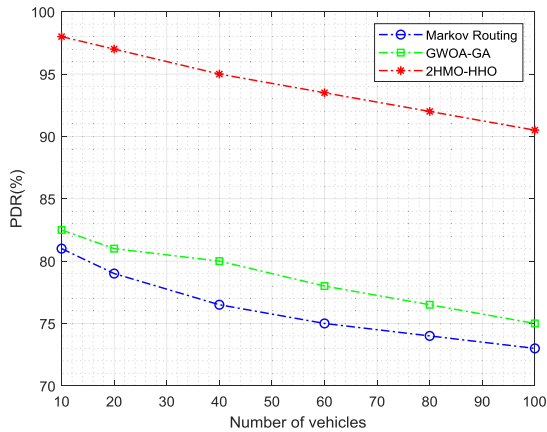


FIGURE 8. Comparison on PDR.

number of nodes is raised. Consequently, several packets are lost due to collision. We have achieved PDR 90-98%, while previous works achieved 75-83% and 74-81%, respectively. Our works achieved around 15% better result compared to those prior works. Though PDR is decreased as the number of vehicles is increased, our work maintains a good PDR. This is due to the stable routing and re-routing. Here, the packet drop is lesser as it does not go for selecting the whole route. Selecting the entire route and maintaining the same route in the dynamic CR-VANET environment is very troublesome due to the vehicle’s high-speed mobility and frequent network changes. 2-hop selection alleviates such problems. This is the primary reason to achieve a better PDR. Improper routing leads to a large packet loss and hence lower PDR.

3) ANALYSIS OF AVERAGE DELAY

Delay is defined as the time taken by a data packet to reach the destination from the source. The delay is measured as the function of propagation time, waiting time and transmission time.

In Figure 9, the delay is compared concerning the number of vehicles. Delay is an important performance measure that shows the efficacy of the proposed routing and data transmission approach. In the proposed work, the delay is minimized to 6 ms since the available spectrum is utilized by a 2-hop routing algorithm effectually though the number of vehicles is increased. In the proposed work, the optimal route is selected by the 2HMO-HHO algorithm by considering multiple metrics. In the prior research, the delay is increased up to 17 ms due to a lack of optimal routing.

4) ANALYSIS OF PACKET LOSS RATE

Packet loss rate (PLR) is defined as the ratio between the number of packets lost and the total amount of packets transmitted over the network. Packets are dropped or lost if the TTL (time-to-live) reaches zero or if the connection fails to deliver. In Figure 10, PLR is compared based on the number of vehicles.

In this work, PLR is nearly 13% when the vehicle number is 100, which is relatively lower than previous research. In the

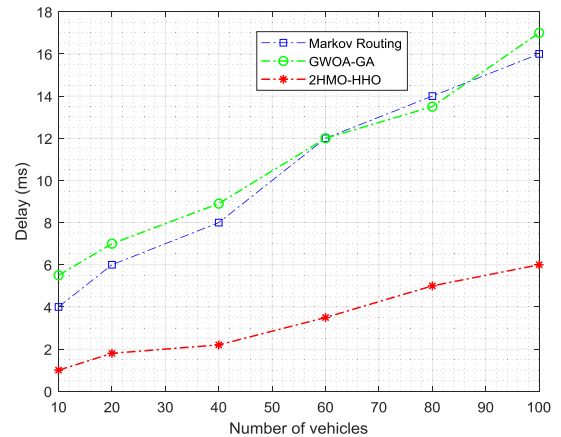


FIGURE 9. Comparison on delay.

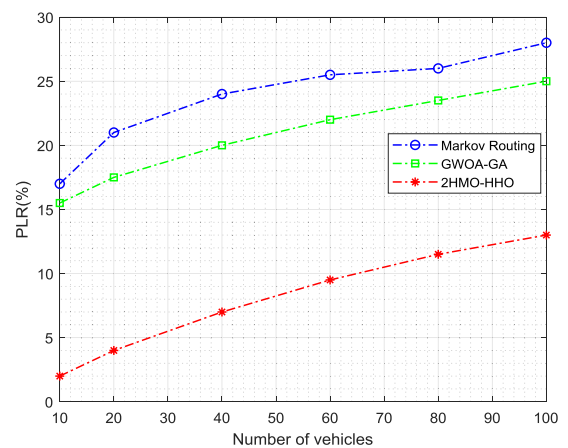


FIGURE 10. Comparison on PLR.

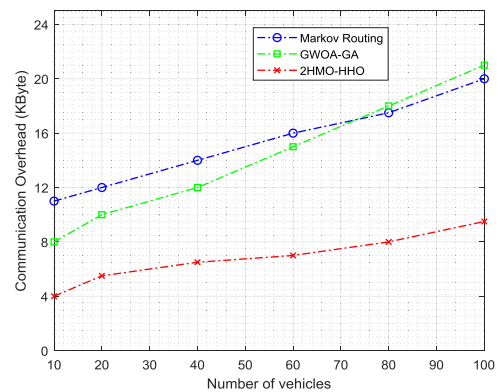


FIGURE 11. Comparison on communication overhead.

proposed work, the optimal 2-hop route is selected for data transmission. Thus, the PLR is lower even with an increase in the number of vehicles. On the other hand, in the Markov routing approach, 28% of packets are lost. In the GWOA algorithm, the entire route is selected in which the vehicles can be dynamic, and the route can be unstable. Thus, the PLR is increased up to 25%. From this analysis, the proposed work improves the PLR by transmitting most of the packets successfully. The packet drop is lower than it does when selecting the entire path.

TABLE 4. Numerical comparison on obtained results.

		Markov Routing	GWOA- GA	2HMO- HHO
Throughput (Mbps)	Mean	12.3	11.75	16.13
	SD	±2.28	±2.42	±1.47
PDR (%)	Mean	78.83	76.41	94.33
	SD	±2.84	±3.07	±1.89
Delay (ms)	Mean	10.0	10.65	3.2
	SD	±4.73	±4.31	±1.94
PLR (%)	Mean	20.58	23.58	7.83
	SD	±3.62	±3.98	±2.29
Network Overhead (KB)	Mean	12.92	12.00	5.78
	SD	±6.49	±6.95	±3.09

5) ANALYSIS OF COMMUNICATION OVERHEAD

Communication overhead is the number of control messages sent to construct and manage the routes by routing protocols. We have again compared our work with two previous works, Markov routing [14] and GWOA-GA [15]. Figure 11 represents a communication overhead for a variable number of nodes. The communication overheads of all routing protocols grow as the number of vehicles increases. Since Markov routing and GWOA-GA routing protocols do not forecast a reliable path, it generates more communication overhead due to frequent route reconstruction. Stable routes are determined by the 2HMO-HHO routing algorithm instead of Markov routing and GWOA-GA routing algorithms. Hence, there is less communication overhead associated with it. For example, when the number of vehicles is 60, 2HMO-HHO needs to exchange around 7 Kbytes of a control message or communication overhead, while GWOA-GA needs 15 and Markov routing needs 16 Kbytes of data. That means more than 50% lesser communication overheads are required for our routing scheme. 2HMO-HHO routing algorithm selects the best 2-hops as the forwarders instead of selecting the entire route from source to destination. It does not need to communicate with all available vehicles for routing process. Therefore, the overall communication overhead is comparatively lesser than those of the previous works.

C. DISCUSSION

Table 4 summarizes the numerical results obtained by the proposed and existing works.

The obtained results are summarized with mean and standard deviation (SD) values. It can be noted that the proposed 2HMO-HHO achieves better results in all metrics due to optimum route management involvement. Proposed 2-hop routing improves data transmission performance effectually. Optimal 2-hop forwarders are selected using the MO-HHO algorithm that takes multiple metrics for forwarder selection to enable optimal data transmission from the source to destination.

D. COMPUTATIONAL COMPLEXITY

Three basic components characterize the computational complexity of HHO: population size N , problem dimensions D ,

and the number of iterations U . On the other hand, the computational complexity of HHO depends on three processes: i) initialization, ii) evaluating fitness function, and iii) updating the position of the hawks (vehicles). The computational complexity of these three processes can be written as:

- i) The computational complexity of the initialization process: $O(N)$
- ii) The computational complexity of the fitness function evaluation: $O(N \times U)$
- iii) The computational complexity of the Hawks location update (including searching for the best location and updating the location vector of all hawks): $O(N \times U) + O(N \times U \times D)$

Therefore, the computational complexity of 2HMO-HHO can be written as,

$$O(HHO) = O(N) + O(N \times U) + O(N \times U) + O(N \times U \times D)$$

Markov-routing [14] 's computational complexity is $O(K \times N)$, where N is the number of nodes in CR-VANETs, and K is the number of road segments. GWOA-GA routing algorithm [15] used a whale optimization algorithm, a tree-based routing protocol, and an optimal link-state routing protocol (OLSR). Therefore, the total computational complexity of the GWOA-GA routing algorithm is $O(N \times U) + O(E \log N) + O(N)$. Here, N represents the population size (nodes), U represents the maximum number of iterations, and E is the number of links between the nodes.

VI. CONCLUSION

This paper has proposed a routing protocol for the cognitive radio-based vehicular ad hoc network (CR-VANET). After the spectrum sensing, the vehicle would find the vacant spectrum. The roadside unit (RSU) would then assign that empty channel to the vehicles. Data transmission is carried through the optimal 2-hop neighbors on the assigned channel selected by the bio-inspired 2-Hop Multi-Objective Harris Hawks Optimization (2HMO-HHO) algorithm. The proposed algorithm has been implemented through simulation in OMNet++ and with SUMO. We have found better results compared to the previous works. We have achieved better throughput, higher packet delivery ratio, lesser packet loss rate, lower delay, and lower network overhead.

In future, we will intend to perform predictive 2-hop neighbor selection to minimize the packet loss further and to reduce the computational complexity. We will incorporate several physical layer characteristics such as shadowing, Doppler fast fading, etc., to make the algorithm more realistic and robust. We will also integrate an optimal resource allocation scheme for vehicles by considering multiple parameters.

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