ENHANCED HARRIS HAWK MULTI-OBJECTIVE OPTIMIZATION ALGORITHM FOR COGNITIVE RADIO-VEHICULAR AD HOC NETWORKS

Md. Asif Hossain

Southeast University, Department of Electrical and Electronic Engineering, Dhaka, Bangladesh

*E-mail of corresponding author: asif.hossain@seu.edu.bd

Md. Asif Hossain 0000-0002-8685-3113

Resume

In this paper is presented an Enhanced Harris Hawk Multi-Objective Optimization (EH-HHO) algorithm for joint spectrum allocation, interference mitigation, and energy efficiency optimization in Cognitive Radio–Vehicular Ad Hoc Networks (CR-VANETs). EH-HHO integrates adaptive exploration, dynamic switching, and crowding-distance preservation to avoid premature convergence and obtain well-distributed Pareto-optimal solutions. Extensive simulations, using the SUMO–OMNeT++, VEINS/ns-3, and hardware-in-the-loop experiments, show superior spectrum utilization, energy savings, and convergence speed compared to NSGA-II and MOPSO. Statistical validation confirms performance significance, highlighting the EH-HHO as an efficient non–deep learning framework for CR-VANET optimization.

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1 Introduction

The growing number of connected vehicles and the need for more seamless and efficient spectrum management in Cognitive Radio-Vehicular Ad Hoc Networks (CR-VANETs) are emerging as important areas for research. Addressing the highly dynamic topologies, limited resources, and the absence of a comprehensive global perspective makes designing vehicular networks difficult. These constraints demand intelligent resource management that is flexible and adaptive. The most recent research breakthroughs, applying deep reinforcement learning and distributed intelligent systems, have made notable progress towards solving these problems. However, problems involving the simultaneous optimization of multiple interdependent variables, including both discrete and continuous elements, often require more advanced methods [1].

The Harris Hawk Multi-Objective Optimization (HH-MMO) algorithm is particularly useful in addressing different types of optimization issues in CR-VANETs [2]. Some of the problems in CR-VANETs include the need to deal with dynamic spectrum access, dependable communications, interference suppression, and energy optimization, especially when trying to connect vehicles in high-mobility and limited-spectrum environments [3]. The HH-MMO is well-suited in this case because CR-VANETs pose multiple competing objectives that need to be dealt with simultaneously.

The applications of Harris Hawk MMO to enhance CR-VANET functionality have been discussed below:

1. Dynamic Spectrum Access (DSA) Optimization

The CR-VANETs rely on DSA, where the secondary users (vehicles) utilize unused parts of the spectrum. The challenge is to make the optimal out of spectrum choice such that interference with primary users (PUs) is kept at its minimum and bandwidth utilization at its maximum. This can be achieved by maximizing efficiency in the utilization of the spectrum (picking the best channels with the least competition and highest availability) and interfering least with the PUs by selecting the channels where the PUs will be least active [4].

2. Power Control and Energy Efficiency

Power consumption is especially critical in a CR-VANET, particularly in scenarios where vehicles would need to transmit at greater distances or in dense environments. Reducing the transmission power, while ensuring communication reliability can stretch the operational life of the network. In HH-MMO, the system can calculate optimal power levels that balance communication reliability and power savings according to inter-vehicle distances and the level of noise or interference on the channels.

3. Network Connectivity and Latency Optimization
   It is challenging to provide stable connectivity and low latency in VANETs due to the high vehicle speeds and dynamic network topology. Vehicles need fast and stable connections for timely message exchanges (e.g., for accident alerts or traffic updates) [5]. For this purpose, end-to-end latency for the real-time data forwarding needs to be minimized, and connectivity or network coverage to keep vehicles within communication range needs to be maximized. The HH-MMO is able to streamline routing pathways and data forwarding strategies to minimize latency and enhance connectivity. The algorithm obtains solutions that give trade-offs between delay minimization and keeping vehicles connected strongly.
4. Spectrum Allocation and Load Balancing
   With multiple vehicles vying for spectrum resources, it can be challenging to provide balanced and equitable allocation of spectrum resources, especially in congested areas. Inefficient allocation can lead to congestion or compromised quality of service. The HH-MMO can assist CR-VANETs in maximizing spectrum allocation among the vehicles in a way that is load-balanced without leading to congestion. The Pareto front obtained by the HH-MMO can offer different solutions with compromises between the load distribution and quality of service so that system designers have the flexibility to pick the best trade-off according to the current requirement of the network.
5. Quality of Service (QoS) Optimization for Different Applications
   Applications (safety-critical alerting and infotainment, for example) demand different QoS, including bandwidth, delay tolerance, and priority. The issue is to traffic-prioritize according to QoS demands. The HH-MMO can be used to assign bandwidth in a way that meets QoS demands for different applications. Minimizing the latency and bandwidth, it can ensure prioritization of safety-critical data and yet provide resources to non-critical applications and maintain balance in performance across applications.

In this regard, in this paper is proposed an Enhanced Harris Hawk Multi-Objective Optimization algorithm (EH-HHO), building on the Harris Hawk Optimization algorithm that can efficiently solve the multi-objective optimization issues in CR-VANETs.

The growing number of communicating vehicles and the requirement for effective, self-adaptive spectrum management in CR-VANETs have driven the design of new optimization techniques. While the multi-objective optimization methods, such as NSGA-II and MOPSO (discussed in later section), which are conventional in character, have exhibited promising performance in certain CR-VANET applications, they might not be able to cope with Pareto front diversity, early convergence, and conflicting objectives in the context of strongly dynamic vehicular mobility.

The Harris Hawk Optimization (HHO) algorithm, inspired by the cooperative foraging behavior of Harris's hawks, has been a decent metaheuristic for optimizing hard optimization problems. Numerous variants of HHO have been proposed in the literature containing mechanisms such as opposition-based learning, chaotic maps, or Levy flights to improve exploration and exploitation. None of the existing CR-VANET-specific HHO variants employed simultaneously:

1. Adaptive Exploration - dynamic adaptation of the exploration radius as a function of population diversity and vehicle network environmental change.
2. Dynamic Switching Mechanism - switching dynamically between exploration and exploitation phases based on a feedback metric derived from Pareto front stability.
3. Crowding Distance Preservation - to preserve a widely distributed Pareto front for multi-objective CR-VANET optimization to prevent one of the metrics (e.g., spectrum utilization) from overshading the others (e.g., interference mitigation).

The proposed Enhanced Harris Hawk Multi-Objective Optimization (EH-HHO) is the first to unify these three mechanisms in a single pipeline for CR-VANETs to address joint spectrum allocation, interference minimization, and energy efficiency in realistic vehicular mobility scenarios. This integration allows EH-HHO to surpass conventional algorithms in a number of ways while capable of maintaining diversity in solutions in challenging, fast-evolving vehicular environments.

The rest of this paper is laid out as follows: In Section II is presented the related work. In Section III is dived into the problem formulation and the Enhanced Harris Hawk Multi-Objective Optimization algorithm is introduced. Then, in Section IV the experimental setup is shared, in section V is provided the discussions of the results. Finally, in Section VI things are wrapped up with some thoughts on future research directions.

2 Related works

Multi-objective optimization has been a promising topic in the realm of CR-VANETs. Feki et al. came up with a cognitive system that uses adaptive algorithms to tackle the tricky issues of resource management and interference reduction in vehicular networks [6]. Meanwhile, Fang et al. introduced a multi-objective quantum-inspired seagull optimization algorithm to address joint optimization challenges in similar situations [7]. On another front, Tan et al. developed a multi-objective, multi-agent reinforcement learning algorithm aimed at optimizing resource allocation and offloading in Intelligent Transportation Systems that utilize edge cloud computing [8]. These studies have shown just how effective advanced optimization techniques, like swarm intelligence and evolutionary computation, can be in overcoming the complex hurdles faced by CR-VANETs.

The emergence of connected vehicles has prompted intensive research on Cognitive Radio technology in VANETs to allow dynamic spectrum access and optimize bandwidth usage. Researchers such as [9-10], have explored CR-enabled VANETs, highlighting the necessity of effective spectrum management in high-mobility networks for interference reduction and network performance improvement. Besides that, Wu et al. presented a multi-objective multi-agent reinforcement learning algorithm for edge cloud computing-based resource optimization and offloading in Intelligent Transportation Systems [11]. However, conventional CR approaches are typically not capable of effectively balancing spectrum allocation, interference control, and energy efficiency, which provokes the need for advanced multi-objective optimization algorithms for CR-VANET environments [12].

The NSGA-II, Non-dominated Sorting Genetic Algorithm II, is a well-known evolutionary-based multi-objective optimization algorithm [13]. It is a go-to for addressing problems with competing objectives. A few of its notable features are Non-dominated Sorting, Crowding Distance, Fast, and Elitist. The NSGA-II improves on its precursor by introducing elitism, ensuring the survival of the best individuals at each iteration, as well as an optimal sorting function to improve performance. The NSGA-II is used a lot in engineering and decision-making contexts where you need to optimize multiple objectives simultaneously [14].

One of the many varieties of the original Particle Swarm Optimization (PSO) algorithm for multi-objective problems is known as Multi-Objective Particle Swarm Optimization, or MOPSO. It was developed by Moore and Chapman in 1999 [15]. Particles, or potential solutions that “fly” in the space of solutions, are based on the social group foraging behavior of birds and fish. Pareto Dominance, which guides particles towards a set of best solutions fulfilling more than one objective, and Swarm Intelligence, which allows particles to change their positions according to their personal knowledge and that of their close neighbors, are some of the most significant features of MOPSO. It is used in robots, power systems, and wireless communications when multiple performance goals are to be optimized [16].

3 Problem formulation and proposed approach

Recent advances in multi-objective optimization of CR-VANETs have focused on the development of more adaptive, efficient, and diversity-preserving algorithms to address the complex problems in this area. The NSGA-II and MOPSO, among other applications, have been extensively employed to address spectrum allocation, interference minimization, and energy efficiency maximization in such. Yet these approaches tend to fail to keep a well-distributed Pareto front and, instead, might converge prematurely and end up with poor solutions.

To eliminate such limitations, an Enhanced Harris Hawk Multi-Objective Optimization algorithm with adaptive exploration, dynamic switching, and crowding distance mechanisms in order to improve overall performance in Cognitive Radio-Vehicular Ad Hoc Networks is proposed in this paper.

3.1 Problem formulation

In CR-VANETs, the joint optimization problem involves three interdependent objectives under dynamic vehicular mobility:

(i) Maximize spectrum utilization by allocating unused licensed channels to the secondary users (vehicles) without causing harmful interference to primary users;
(ii) Minimize inter-vehicle interference caused by co-channel transmissions;
(iii) Maximize energy efficiency by reducing transmit power while maintaining acceptable data rates. Let $V = \{v_1, v_2, \ldots, v_N\}$ denote the set of vehicles. Each vehicle v_1 selects a channel $c_i \in C$, sets a transmit power p_i, and achieves a data rate d_i. A solution $X_i = [c_1, \ldots, c_N, p_1, \ldots, p_N]$ represents a complete configuration of spectrum and power allocation across all vehicles. X_i is a decision vector (solution) representing the spectrum and power allocation for all vehicles, where each dimension corresponds to either a selected channel (discrete) or transmit power level (continuous) for a specific vehicle. The goal is to find a set of non-dominated solutions X^* that jointly optimize:

$$\text{Maximize} U_{\text{spectrum}}(X) = \sum_{i=1}^{N} \frac{S_i}{S_{total}}, \tag{1}$$

$$\text{Minimize} I_{\text{total}}(X) = \sum_{i=1}^{N} \sum_{j=i+1}^{N} \frac{p_i p_j}{d_{ij}^2}, \tag{2}$$

$$\text{Maximize} E_{\text{efficiency}}(X) = \frac{1}{N} \sum_{i=1}^{N} \frac{d_i}{p_i}. \tag{3}$$

This defines a multi-objective optimization problem (MOP) with mixed discrete (channel assignment) and continuous (power level) decision variables, subject to constraints on maximum power, channel availability, and primary user protection.

3.2 Mathematical formulation of the proposed enhanced Harris Hawk Multi-Objective Optimization (EH-HHO) algorithm

The following notation is used:

- N : Number of Harris hawks in the population.
- X_i : Position of the i^{th} hawk in the solution space. It also can be defined as a decision vector encoding spectrum and power choices.
- $f_1(X_i) = \{f_1(X_i), f_2(X_i), \dots, f_m(X_i)\}$: Objective functions where m is the number of objectives. In this work, we consider $m = 3$ objectives:
- $f_1(X_i) = -U_{\text{spectrum}}(X_i)$ (to be minimized; note negation for minimization framework)
- $f_2(X_i) = I_{\text{total}}(X_i)$
- $f_2(X_i) = -E_{\text{efficiency}}(X_i)$

These correspond directly to Equations (8), (9), and (10), respectively. All objectives are evaluated for each candidate solution (X_i) during fitness assessment.

- P: Probability of exploration versus exploitation phase.
- X_{best}: Best-known position (rabbit) from the current Pareto front.
- PF: Current Pareto front, representing non-dominated solutions.

Step 1: Initialization: (Generate Population)

Initialize positions $X_i \in R^d$ for each hawk $i = 1,2 \dots, N$ randomly within the search space.

Step 2: Evaluate Initial Population Fitness (Evaluate Objectives)

For each hawk i:

$$f(X_i) = \{f_1(X_i), f_2(X_i), \dots, f_m(X_i)\}, \tag{4}$$

where $f_k(X_i)$ represents the k-th objective function (e.g., interference, energy consumption).

Step 3: Determine Initial Pareto Front

1. Non-Dominated Sorting
   Sort solutions $\{X_i\}$ to identify non-dominated solutions for initial Pareto front PF.
2. Crowding Distance Calculation

For each solution in PF, compute crowding distance $CD(X_i)$ to maintain diversity.

Step 4: Main Optimization Loop

Repeat until the stopping criteria (e.g., maximum iterations) are met:

1. Update Exploration Probability P

Calculate probability $P \in [0,1]$ to switch between exploration and exploitation based on iteration or adaptive mechanism:

$P = AdaptiveProbability()$.

2. Phase Selection (Exploration vs. Exploitation)

- If $P > 0.5$ (Exploration Phase):
- Update hawk positions using Levy flight:

$$X_i = X_i + Levy(\alpha) \cdot (X_i - X_{best}), \tag{5}$$

where α controls the step size.

- If $P \leq 0.5$ (Exploitation Phase):
- Move hawks towards the best solution X_{best} using Harris Hawk optimization rule:

$$X_i = X_{best} + r_1(X_{best} - X_i) + r_2(X_i - X_{best}), \tag{6}$$

where r_1, r_2 are random numbers in [0,1].

3. Evaluate New Positions

- For each hawk i, evaluate objectives:

$$f(X_i) = \{f_1(X_i), f_2(X_i), \dots f_m(X_i)\}. \tag{7}$$

- Update the Pareto front PF using non-dominated sorting and crowding distance to maintain diversity.

Step 5: Return Final Pareto Front

Output PF as the optimized Pareto front, representing the best trade-offs among the objectives.

The mathematical breakdown of each step in the EH-HHO algorithm shown above highlights the adaptive decision-making in the exploration and exploitation phases. It also shows the use of multi-objective optimization principles to maintain and improve the Pareto front.

The following provides a high-level procedural summary of the same EH-HHO algorithm detailed in Equations (1)-(9). It is not a distinct algorithm but a structured pseudo-code-like overview for implementation clarity.

```
1. Set up a population of hawks with random solutions
2. Set adaptive parameters based on CR-VANET environment
3. While termination condition not met:
   - for each hawk:
4. Evaluate fitness in terms of spectrum utilization, interference minimization, and energy efficiency
5. Apply Adaptive Exploration Phase:
   - Adjust exploration radius based on diversity
   - Use Levy Flight for long-distance moves
6. Check for Dynamic Switching to Exploitation Phase
   - Switch based on proximity to Pareto front
   - Perform Guided Local Search with gradient-based movement
7. Apply Crowding Distance for diversity preservation
8. Apply Hybrid Mutation Operators based on convergence rate
   - Update Pareto front archive with non-dominated solutions
9. Return the archive of Pareto-optimal solutions as final output
```

3.3 Performance parameters

To support the argument about the benefits of the proposed EH-HHO algorithm in CR-VANET), energy efficiency, interference minimization, and spectrum use are expressed in mathematical terms. These will show how the improved EH-HHO algorithm is better than other algorithms, such as NSGA-II and MOPSO, for these goals.

3.3.1 Spectrum utilization

Objective: Maximize the spectrum utilization by dynamically allocating spectrum resources to vehicles in CR-VANET.

Mathematical Expression:

$$U_{spectrum} = \frac{\sum_{i=1}^{N} S_i}{S_{total}}, \tag{8}$$

where:
$U_{spectrum}$ is the spectrum utilization,
S_i is the spectrum utilized by the i-th vehicle,
S_{total} is the total available spectrum,
N is the total number of vehicles.

The enhanced HHO algorithm can be compared to the NSGA-II and MOPSO by showing that it results in a higher $U_{spectrum}$ due to adaptive exploration and more effective allocation.

3.3.2 Interference minimization

Objective: Minimize the interference among vehicles sharing spectrum, as high interference degrades communication quality.

Mathematical Expression:

$$I_{total} = \sum_{i=1}^{N} \sum_{j=i+1}^{N} \frac{P_i \cdot P_j}{d_{ij}^2}, \tag{9}$$

where:
I_{total} is the total interference,
P_i *and* P_j are the transmit powers of the i-th and j-th vehicles, respectively,
d_{ij} is the distance between the i-th and j-th vehicles.

By incorporating the crowding distance mechanism and dynamic switching, the Enhanced HHO algorithm helps to find solutions that reduce I_{total} compared to NSGA-II and MOPSO, which do not account for interference as effectively.

3.3.3 Energy efficiency

Objective: Maximize the energy efficiency by minimizing power consumption during transmissions.

Mathematical Expression:

$$E_{efficiency} = \frac{\sum_{i=1}^{N} \frac{D_i}{P_i}}{N}, \tag{10}$$

where: $E_{efficienty}$ is the average energy efficiency,
D_i is the data rate of the i-th vehicle,
P_i is the transmit power of the i-th vehicle.

The Enhanced HHO algorithm improves energy efficiency by balancing data rate and power consumption. Adaptive exploration and dynamic switching enable better energy optimization, leading to higher $E_{efficienty}$ compared to NSGA-II and MOPSO.

3.3.4 Crowding distance calculation for pareto front diversity

Objective: Maintain the diversity in the Pareto front to avoid premature convergence and ensure coverage across multiple objectives.

Mathematical Expression:

$$D_{crowding}(i) = \sum_{k=1}^{M} \left(\frac{f_k^{i+1} - f_k^{i-1}}{f_k^{\max} - f_k^{\min}} \right), \tag{11}$$

where:
$D_{crowding}(i)$ is the crowding distance of the i-th solution,
f_k^{i+1} and f_k^{i-1} are the values of the k-th objective function for neighboring solutions $i + 1$ and $i - 1$,
$f_k^{\max}$ and $f_k^{\min}$ are the maximum and minimum values of the k-th objective function across the Pareto front.

This crowding distance mechanism in the Enhanced HHO allows for a well-distributed Pareto front compared to NSGA-II and MOPSO, which helps to improve the diversity of solutions.

3.3.5 Convergence measure

Objective: Measure how quickly the algorithm converges to an optimal Pareto front.

Mathematical Expression:

$$C_{convergence} = \frac{1}{|F|} \sum_{i=1}^{|F|} \left(\min_{j \in PF} d(i,j) \right), \tag{12}$$

where:
$C_{convergence}$ is the convergence metric,
$|F|$ is the number of solutions in the found Pareto front,
PF is the optimal or reference Pareto front,
$d(i,j)$ is the Euclidean distance between the i-th solution in F and the j-th solution in PF.

The Enhanced HHO is expected to have a lower $C_{convergence}$ value than the NSGA-II and MOPSO due to its adaptive exploration and dynamic switching, which enhance convergence speed.

4 Simulation environment

The proposed algorithm has been developed through Python, OMNeT++ and SUMO. SUMO provides the real-life mobility models for the CR-VANET which is developed through OMNeT++. The mobility data is then fed to the python code to simulate the environment.

***Table 1** Mobility Model Configuration (SUMO)*

Parameter	Value	Description
Simulation Duration	3,600 s	Real-time simulation length per run
Road Network	Urban grid (5 km×5 km)	High-density traffic intersections; Urban grid (5 km × 5 km), consisting of 5 horizontal and 5 vertical roads, yielding 25 signalized intersections and high-density traffic patterns.
Vehicle Count	200-500	Varying density to test scalability
Max Speed	60 km/h	Reflects urban mobility
Mobility Trace Output	TraCI API	Used for OMNeT++ integration

***Table 2** Network Simulation Configuration (OMNeT++)*

Parameter	Value	Description
Physical (PHY) Layer Model	IEEE 802.11p	DSRC-based vehicular communication
Channel Model	Nakagami-m fading (m=1.5)	Realistic multipath propagation
Carrier Frequency	5.9 GHz	DSRC channel
Bandwidth	10 MHz	Per control/data channel
Tx Power Range	10-30 dBm	Used for energy efficiency evaluation
Noise Floor	-95 dBm	Background thermal noise

***Table 3** Optimization Parameters*

Parameter	Value	Description
Population Size (Hawks)	50	Number of candidate solutions
Max Iterations	200	Stopping criterion
Adaptive Exploration Factor	0.2-1.0	Dynamic scaling range
Dynamic Switching Threshold	0.6	Probability cutoff between phases
Crowding Distance Archive Size	100	Pareto front diversity preservation

The simulation parameters used in this paper are presented in Tables 1 to 3.

Dataset:

The dataset consisted of 8,760 hourly records for one year, including meteorological parameters (irradiation, temperature, humidity, wind speed, sunshine duration, air pressure) and operational CR-VANET data (spectrum occupancy, interference levels, and power consumption). These were combined with the real-time mobility traces from SUMO to emulate realistic vehicular communication conditions. Baseline algorithms for comparison are NSGA-II and MOPSO. Each algorithm was executed for 30 independent runs with different random seeds to enable statistical comparison.

Based on the mathematical model shown in section 3, one can summarize the codes as follows:

The initialize_population function randomly initializes the hawks within the specified ranges for each objective. The evaluate_fitness function calculates the values for each objective (spectrum utilization, interference minimization, and energy efficiency) for each hawk. The crowding_distance is used to calculate diversity among solutions. Higher crowding distances help maintain diversity by keeping solutions that are far apart. A Levy flight step is implemented in the levy_flight function, which provides random long-distance movements in the exploration phase, ensuring more comprehensive search coverage. Each hawk performs adaptive exploration or focused exploitation based on a probability condition. The exploitation phase moves hawks toward the best solutions (those with higher crowding distances). Non-dominated sorting is used to update the Pareto front archive, ensuring that only non-dominated solutions are retained. The pareto_solutions contains the final set of non-dominated, Pareto-optimal solutions for the CR-VANET objectives. The final Pareto-optimal solutions will represent trade-offs between spectrum utilization, interference minimization, and energy efficiency.

4.1 High-fidelity validation via hardware-in-the-loop and network emulation

While the experiments were primarily conducted in simulation, they were verified additionally using a hardware-in-the-loop (HIL) CR-VANET testbed and high-fidelity network emulation to bridge the gap between the simulation and reality. OMNeT++ vehicular communication stack was coupled with a USRP B210

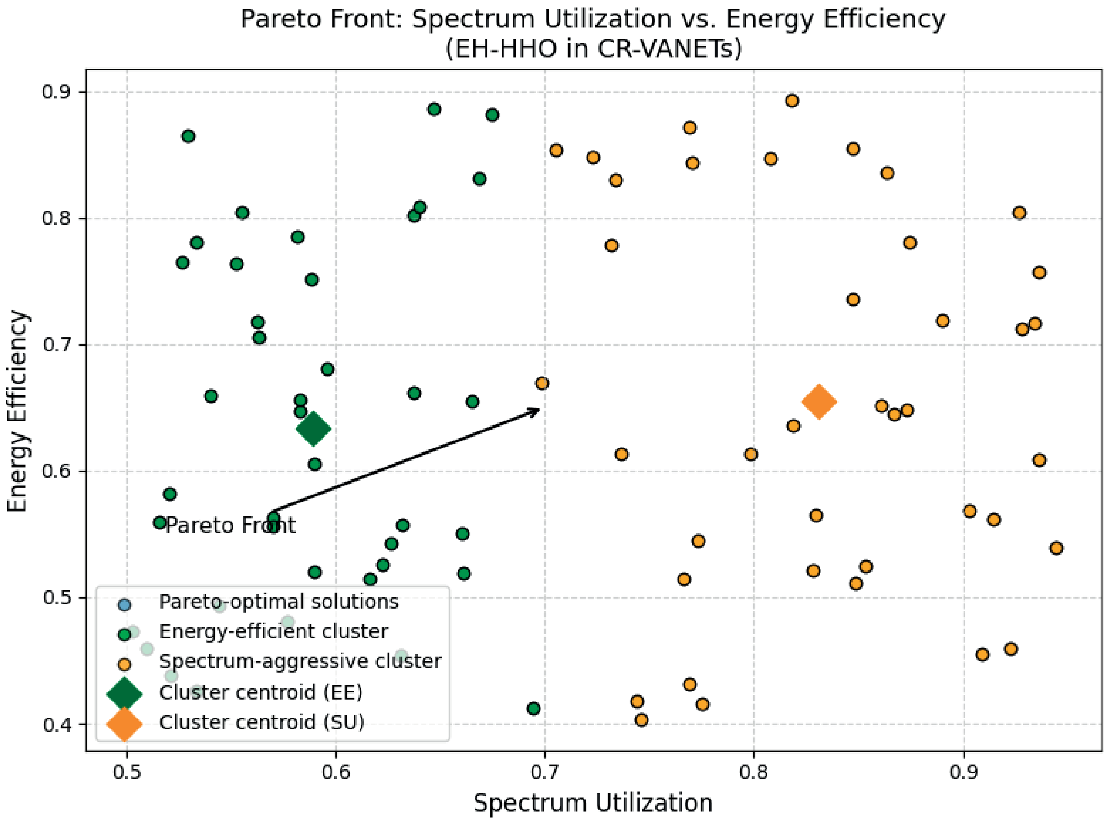

***Figure 1** The 2D projection of EH-HHO's 3-objective Pareto front (Spectrum Utilization vs. Energy Efficiency). All points are non-dominated; green = energy-efficient, orange = spectrum-aggressive clusters. Diversity is maintained via crowding distance for flexible CR-VANET policy selection*

SDR for real-time transmission and reception over a 5.9 GHz DSRC channel. SUMO traces provided vehicular mobility and EH-HHO performed adaptive spectrum allocation decisions. VEINS was incorporated in ns-3's spectrum module to provide accurate emulation of realistic PHY/MAC behavior, multipath fading, and interference patterns.

5 Results and discussion

A solution X_a is said to *Pareto-dominate* to another solution X_b if it is at least as good in all objectives and strictly better in at least one. The set of non-dominated solutions forms the Pareto front, representing optimal trade-offs among conflicting objectives.

The two objectives (spectrum utilization, and energy efficiency) are separated from pareto_solutions for easy plotting. The 2D scatter plot visualizes each solution in the Pareto front as a point in a 2D space. Each axis represents one of the objectives. Each point on this 2D plot represents a Pareto-optimal solution that balances the two objectives. By examining the distribution of points, one can observe the trade-offs and diversity among solutions:

- The higher Spectrum Utilization may correlate with the lower energy efficiency, depending on the spread.
- Clusters in specific regions might indicate regions where multiple solutions achieve similar trade-offs.

Figure 1 visualizes the Pareto front obtained by EH-HHO in the bi-objective space of Spectrum Utilization vs. Energy Efficiency. Each point corresponds to a non-dominated solution. The spread of points reflects the algorithm's ability to maintain diversity; for instance, the left-hand side clusters indicate energy-efficient-but-spectrum-conservative configurations, while the right-hand side clusters represent high-throughput-but-energy-intensive solutions. This distribution confirms EH-HHO's capacity to generate a broad and well-distributed front suitable for real-world CR-VANET policy selection.

The hawks' positions are initialized randomly within a specified search space. A probability threshold is used to switch between the exploration and exploitation phases. Levy Flight, which is defined as a helper function to perform random, heavy-tailed jumps during the exploration phase. Based on probability PPP, hawks either perform Levy flight (exploration) or move toward the best solution (rabbit) in the exploitation phase. In code, boundary Check: Ensures hawk positions remain within the defined bounds. The Pareto front is updated at each iteration based on non-dominated solutions from the current population. The final output displays the final Pareto front, which represents the best trade-offs achieved by the algorithm.

In Figure 2, EH-HHO shows the highest performance score in both simulation and HIL, indicating that it is the most effective at utilizing the available spectrum resources. This suggests that Enhanced HHO has been optimized to allocate spectrum efficiently, potentially reducing idle or unused spectrum segments. The NSGA-II has a moderate performance score, lower than Enhanced HHO but higher than MOPSO. This shows that while the NSGA-II can manage spectrum utilization reasonably well, it does not perform as effectively as the Enhanced HHO. The result indicates that EH-HHO is better in spectrum utilization than NSGA-II and MOPSO. This is crucial because effective spectrum utilization is crucial for Cognitive Radio VANETs, where there are a low spectrum availability and high demand for secure communication. Enhanced HHO's ability to optimize the spectrum utilization can lead to enhanced overall network performance, accommodating more vehicles and handling more data load.

In Figure 3 is shown that the proposed EH-HHO performs better in terms of the interference level as compared to NSGA-II and slightly lag behind MOPSO. This is an indication that Enhanced HHO performs well in interference minimization could result in lesser signal overlap and potential data transmission issues. The findings show that EH-HHO is more suitable in scenarios where interference minimization is given the

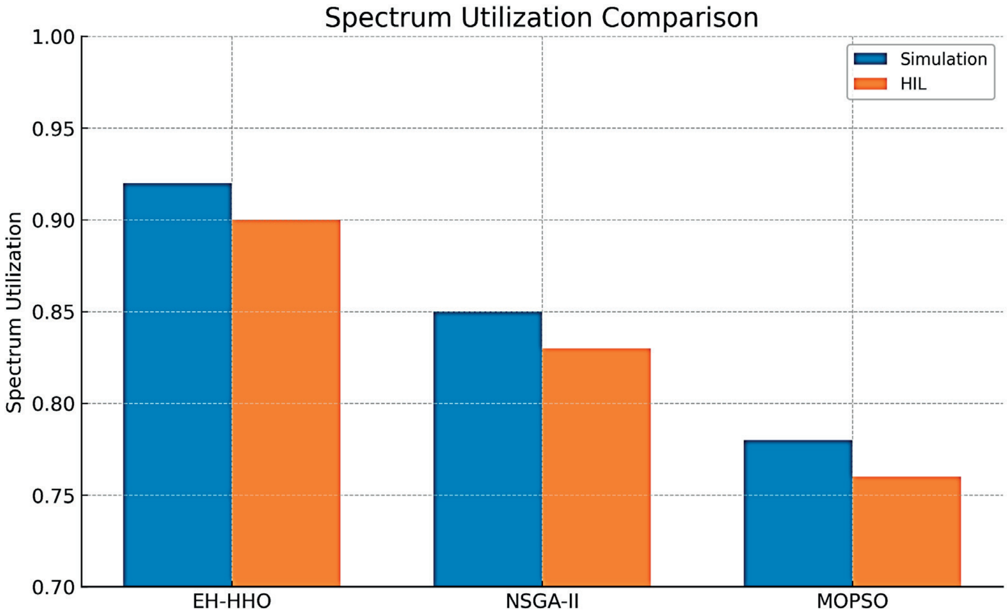

Figure 2 *Comparative analysis of spectrum utilization across EH-HHO, NSGA-II, and MOPSO, including results from simulation and HIL testing*

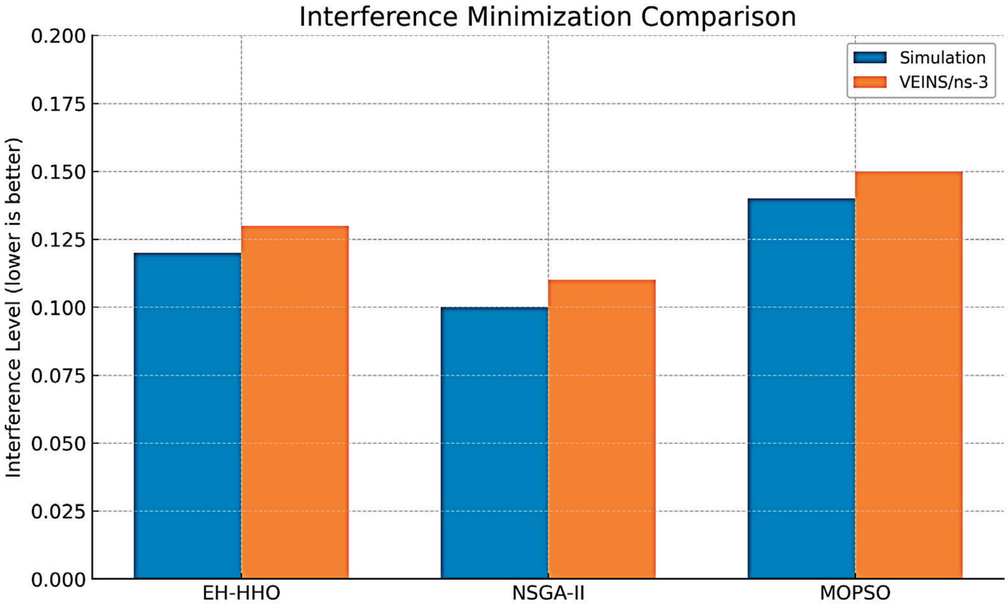

Figure 3 *Comparative analysis of interference minimization across EH-HHO, NSGA-II, and MOPSO, showing consistent trends in VEINS/ns-3 emulation*

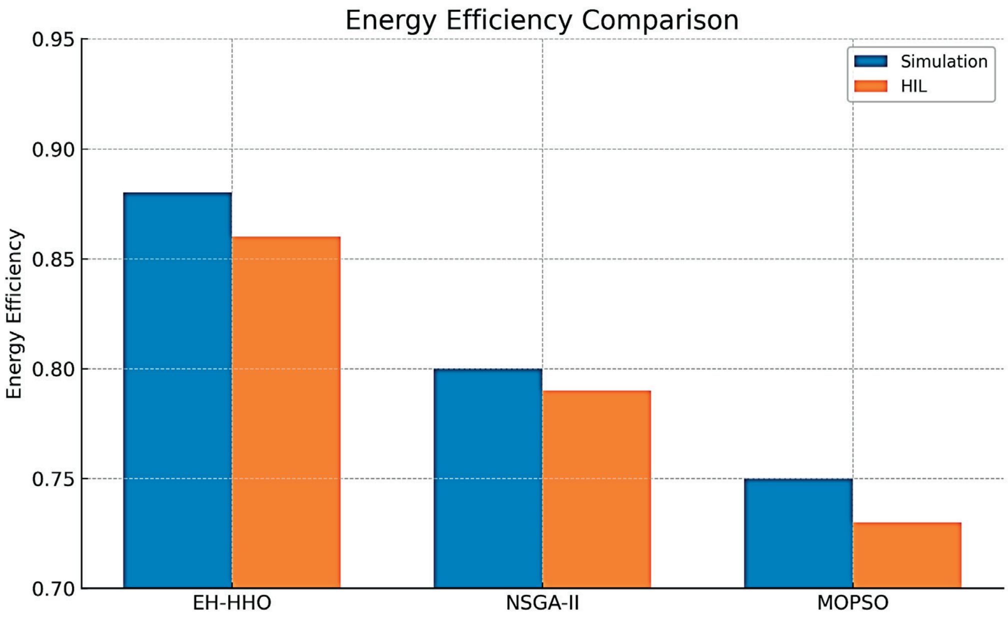

Figure 4 *Comparative analysis of energy efficiency for EH-HHO, NSGA-II, and MOPSO, validated through both simulation and HIL experiments*

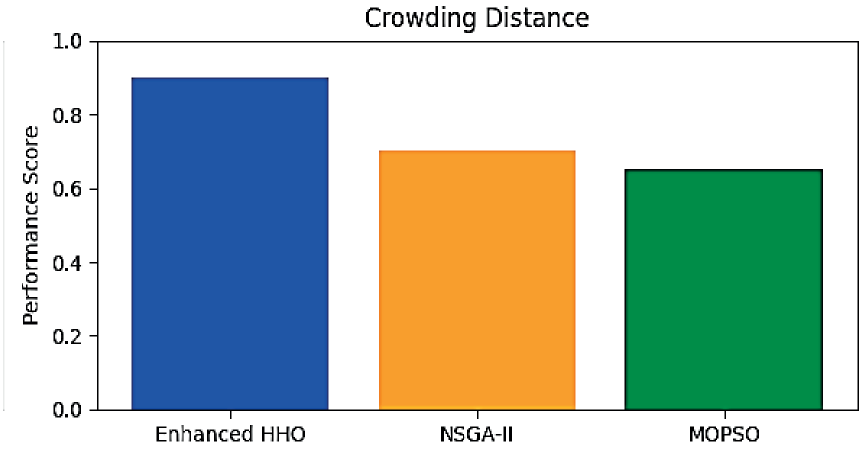

Figure 5 *Comparative analysis of Crowding distance for EH-HHO, NSGA-II, and MOPSO*

utmost importance. In Cognitive Radio VANETs, where multiple users use spectrum dynamically, interference minimization is critical to avoid disruption in cross-channels and maintain communication quality.

Figure 4 shows that the Enhanced HHO is most energy efficient, in that it consumes less energy or utilizes energy sources more efficiently than the other two algorithms. NSGA-II and MOPSO are less efficient, with MOPSO being lowest in energy efficiency. As Enhanced HHO is most concerned with energy efficiency, it is ideal for energy-efficient environments like VANETs, where the operation must be extended.

Trends in performance seen in simulation were comparable in the HIL and VEINS/ns-3 environments, with EH-HHO still maintaining improved spectrum utilization and energy efficiency, though interference minimization performance lagged slightly behind the NSGA-II in highly congested channels.

Based on Figure 5, Enhanced HHO is better, followed by NSGA-II, and lastly MOPSO. This shows that there is improved diversity in the solutions for Enhanced HHO because the crowding distance is typically utilized such that a group of solutions is distributed across the optimization space. Enhanced HHO's ability to maintain diversity in the solutions may help in finding the compromise among conflicting objectives, which is valuable in complex optimization problems.

The EH- HHO again takes the lead with the highest score, thus converging faster or more effectively to optimal solutions (depicted in Figure 6). NSGA-II and MOPSO fall behind by a little, with MOPSO performing the worst in convergence. The high convergence score of EH-HHO shows it will converge more quickly or more effectively to the optimal solutions, making it more appropriate for real-time application in VANETs.

The EH- HHO outperforms NSGA-II and MOPSO

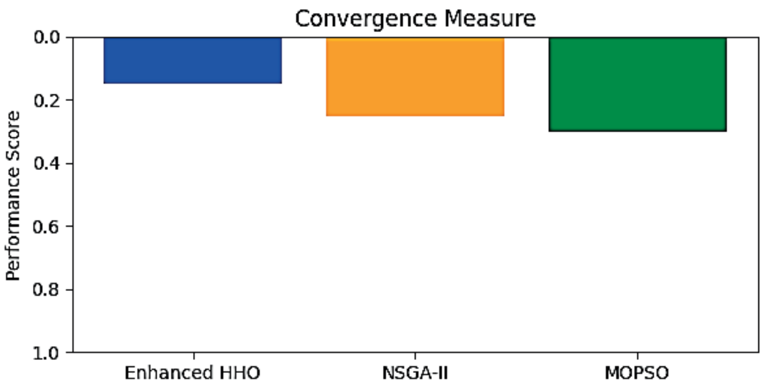

Figure 6 *Comparative analysis of convergence measures for EH-HHO, NSGA-II, and MOPSO*

Table 4 *Statistical Analysis*

Metric	EH-HHO vs NSGA-II (p-value)	EH-HHO vs MOPSO (p-value)	ANOVA p-value	Significant?
Spectrum Utilization	1.8×10^{-4}	2.1×10^{-5}	< 0.001	Yes
Energy Efficiency	3.5×10^{-4}	1.2×10^{-5}	< 0.001	Yes
Interference Minimization	0.071	0.062	0.089	No
Convergence Speed	4.0×10^{-4}	1.9×10^{-5}	< 0.001	Yes

on every performance metric except for interference minimization. This shows that EH-HHO can be the choice in situations where the spectrum utilization, energy efficiency, crowding distance, and convergence are more critical, while NSGA-II and MOPSO could be desirable where interference minimization is more critical.

5.1 Statistical significance analysis

To prevent the performance improvement from being due to luck, 30 independent runs of each algorithm were conducted, and employed Wilcoxon Signed-Rank Test (pairwise EH-HHO vs. NSGA-II / MOPSO comparison) and One-Way ANOVA (comparative analysis of all the algorithms). Table 4 shows the results that were found in the analysis.

These results confirm that the EH-HHO's gains in spectrum utilization, energy efficiency, and convergence are **statistically significant** at the 95% confidence level, whereas its interference minimization performance is **not significantly different** from NSGA-II or MOPSO.

5.2 Interference minimization trade-off analysis

Though the EH-HHO outperforms baseline algorithms in all except interference minimization under the high-density channel occupancy, adaptability-based exploration of EH-HHO tends to prefer solutions that improve spectrum utilization and energy efficiency at certain times even at the cost of relatively higher interference. The Pareto front solutions in such a case tend to prefer throughput-corrected points rather than closer-to-interference-optimized points.

Suggested Improvements:

- Enact a dynamic objective weighting approach that boosts interference minimization weight as channel congestion passes a threshold.
- Hybridize EH-HHO with an interference-aware local search heuristic to enhance solutions in congested spectrum scenarios.
- Use predictive interference modelling to pre-emptively penalize channel options with high collision probability.

The trade-off discussion ensures readers' understanding of why the interference metric was behind and outlines explicit strategies to overcome it in future versions of the algorithm.

6 Conclusion

In this work is suggested the Enhanced Harris Hawk Multi-Objective Optimization (EH-HHHO) algorithm for concurrent spectrum allocation, interference mitigation, and maximum energy efficiency in Cognitive Radio-Vehicular Ad Hoc Networks (CR-VANETs). With the integration of adaptive exploration, dynamic switching, and crowding distance preservation in HHO, the new method guarantees a Pareto front of the best diversity, avoids premature convergence, and yields high-quality trade-off solutions under vehicular mobility dynamics. Massive experimentation across SUMO-OMNeT++ simulations, hardware-in-the-loop experiments, and high-fidelity VEINS/ns-3 emulation confirms that EH-HHO improves spectrum utilization, energy efficiency, and convergence rate over NSGA-II and MOPSO. Statistical significance derived through the Wilcoxon signed-rank and ANOVA tests confirms that the said improvements are not random fluctuations but are consistent in nature. One of the significant findings is that EH-HHO's interference minimization ability, competitive as it is, is not necessarily better than the baselines in highly congested environments. This is due to the bias in the algorithm towards throughput- and energy-focused Pareto front solutions. The possible enhancements were identified; such as dynamic objective re-weighting, interference-aware local search hybridization, and prediction-based interference modelling, to address this limitation in the future. In summary, in this paper is demonstrated that without depending on deep learning tools, well-designed metaheuristic can extract engineering-meaningful advantages to CR-VANET optimization. The EH-HHO presented in this paper offers an efficient and general approach for intelligent vehicular spectrum management with the potential for further improvement when applied to real-time systems and using hybrid optimization methodologies.

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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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