WREN-CR-VANET: Energy-efficient Cluster-based Routing for VANET

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***Abstract*—This paper presents Wren-based Cluster-based Routing for Vehicular Ad-Hoc Networks (WREN-CR-VANET), an energy-efficient, cluster-based routing framework for Vehicular Ad-Hoc Networks (VANETs) that jointly optimises cluster-head selection and multi-hop routing in a single, coupled hierarchical process. Unlike conventional schemes that treat clustering and routing as independent stages, the cluster topology produced during cluster-head selection directly defines the search space for route optimisation, making the two phases interdependent. Optimisation is performed by the Wren Metaheuristic Optimisation Algorithm (WMOA), a vehicular adaptation of the Superb Fairy-wren Optimisation Algorithm, whose adaptive exploration-exploitation mechanism delivers robust convergence with low parameter sensitivity relative to genetic, particle-swarm, and firefly-based methods. A stage-specific multi-objective fitness function guides cluster-head selection using residual energy, inter-vehicular distance, node degree, centrality, and cluster balance. At the same time, routing is optimised based on residual energy, communication distance, and link stability to preserve reliability during mobility. The framework is implemented in MATLAB and evaluated across vehicle densities ranging from 50 to 200. Compared with the Enhanced Cluster-based Lifetime Routing Protocol (ECBLTR), the Hybrid Genetic Firefly Algorithm (HGFA), and Bee-Foraging Learning Particle Swarm Optimisation (BFL-PSO), WREN-CR-VANET improves packet delivery ratio by 15.2%, reduces energy consumption by 21.3%, and extends network lifetime by 18.6%, with these improvements observed consistently across ten independent runs. Future work targets large-scale testbed deployment and security-aware extensions.**

***Keywords*—Vehicular Ad-Hoc Networks (VANET), WREN-CR-VANET, superb fairy-wren optimisation algorithm, energy-efficient clustering, link stability-aware routing, intelligent transportation systems**

I. Introduction

Vehicular Ad-Hoc Networks (VANETs), a specialised class of Mobile Ad Hoc Networks (MANETs), facilitate intercommunication among vehicles through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, supporting the development of an intelligent transport system [1, 2]. VANETs support several applications related to traffic safety, congestion reduction, and even entertainment services. However, due to their high vehicular mobility and dynamically changing topologies, they exhibit poor routing stability, packet losses, and low energy efficiency [3–5].

To address some of the issues, clustering-based routing is proposed to enhance scalability and reduce routing overhead [6–7]. In this case, the selection of appropriate Cluster Head (CH) nodes is crucial for routing stability and energy savings. For this reason, metaheuristic optimisation is widely used, as it can efficiently solve multiple objectives in dynamic environments [8–10].

However, despite these improvements, there are still many challenges. Firstly, almost all current approaches separate clustering and routing processes without accounting for their mutual dependence [11, 12]. Furthermore, pure metaheuristics have problems with exploration and exploitation equilibrium, while hybrid approaches suffer from poor fitness formulation and a bad combination of clustering and routing stages [13, 14]. Besides, restricted fitness functions and simulations decrease applicability in a dynamically changing VANET environment [15–18].

To address these problems, we introduce Wren-based Cluster-based Routing for Vehicular Ad-Hoc Networks (WREN-CR-VANET) a hybrid metaheuristic approach based on the Wren Metaheuristic Optimisation Algorithm (WMOA) [19], our vehicle-oriented version of the Superb Fairy-wren Optimisation Algorithm (SFOA). The developed approach performs joint optimisation of cluster head selection and routing using a multi-objective fitness function that accounts for residual energy, vehicle distance, node centrality, cluster balance, and link stability in the context of mobility.

The main contribution of the presented WREN-CR-VANET architecture can be outlined as follows:

(1) A unified metaheuristic framework for joint clustering and routing optimisation, ensuring compatibility between intra- and inter-cluster decisions.
(2) A multi-objective fitness function incorporating energy, distance, node degree, centrality, and cluster balance for stable and efficient clustering.
(3) Integration of link stability to improve routing reliability under mobility.
(4) Application of WREN-CR-VANET for balanced exploration-exploitation with reduced parameter sensitivity.
(5) Demonstrated performance improvements over baseline routing protocols in simulation studies.

Unlike Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), Firefly Algorithm (FA), and other bee-inspired optimisation approaches commonly used in VANET optimisation, the proposed WREN-CR-VANET

framework does not simply replace one optimisation algorithm with another. Instead, it establishes a coordinated optimisation framework in which clustering outcomes directly influence routing decisions. Moreover, the suggested adaptive exploration-exploitation mechanism enhances solution diversity and reduces parameter dependence, improving adaptability in highly dynamic vehicular network environments.

Unlike conventional VANET routing approaches, in which clustering and routing are separate processes, the proposed solution provides a unified optimisation approach that enhances stability and efficiency in dynamic environments. To the best of the authors' knowledge, the proposed application of WREN-CR-VANET for solving the clustering and routing problem in a vehicular ad hoc network has not been studied previously.

Whereas traditional techniques for optimisation in VANETs separate clustering from routing discovery, the proposed WREN-CR-VANET framework integrates these two operations into a single optimisation strategy. Although separate fitness functions are applied to the specific aims at different stages, both clustering and routing follow a similar strategy to achieve energy savings, reliable communication, and lower overhead. Moreover, the dynamic exploration/exploitation process inherent to the proposed approach provides robust optimisation without being highly dependent on parameters.

The outline of the rest of this paper is as follows. First, relevant literature on VANET routing and clustering approaches is briefly reviewed in Section II. The problem statement is presented in Section III, while the system model is presented in Section IV. The proposed methodology, called WREN-CR-VANET, is described in detail in Section V. Simulation and experimental evaluation results are discussed in Section VI. Finally, conclusions are given in Section VII.

II. Related Work

This section reviews recent research on clustering-based routing and optimisation-driven routing techniques in Vehicular Ad Hoc Networks (VANETs).

A. Cluster-based Routing Techniques

In VANETs, clustering techniques have been widely utilised to achieve scalability, minimise routing overhead, and promote stable communication. The effectiveness of any clustering technique depends heavily on the appropriate selection of Cluster Heads (CHs) and on cluster stability.

A fuzzy inference system has been integrated into cluster formation by Naeem *et al.* [6] to select CHs. Enhanced Cluster-based Lifetime Routing Protocol (ECBLTR) incorporates parameters such as node residual energy, inter-node distances, and node density to promote efficient communication within clusters. Its performance is negatively affected by high mobility within the network.

Hybrid and multi-objective clustering methods have also been considered in recent research to enhance network efficiency. For instance, baseline mobility-aware routing protocols, such as the one proposed by Sirmollo and Bitew [16], are often used to manage these rapid topology changes at the network layer. Alsuhli *et al.* [20] developed a bio-inspired metaheuristic framework for dynamic clustering optimisation in vehicular environments. At the same time, Kaur and Kumar [21] introduced a multi-objective vibrating particle swarm algorithm designed to balance conflicting operational constraints in data clustering. Nevertheless, these methods usually depend only on limited architectural factors and completely ignore the vital role of integrated routing schemes.

Recent studies have made notable advancements in cluster optimisation strategies to enhance network efficiency. For instance, Sajithabegam and Menakadevi [22] proposed an enhanced energy and distance-based adaptive clustering framework to improve stability and control communication overhead in centralised topologies. Similarly, Alazab *et al.* [23] introduced a multi-objective cluster-head selection approach that employs a fitness-averaged rider optimisation algorithm to satisfy diverse constraints in smart-city network deployments. Although these modern approaches significantly optimise clustering metrics and improve overall energy preservation, they generally prioritise cluster structural formations as isolated stages and do not jointly incorporate multi-layered vehicular routing path selections

B. Routing Optimisation Techniques

Routing problems in Vehicular Ad hoc Networks remain a challenge, especially in the dynamic topologies of VANETs due to vehicular mobility; hence, the need to apply metaheuristics.

Singh *et al.* [13] developed the Hybrid Genetic Firefly Algorithm (HGFA). This method integrates the global optimisation properties of Genetic Algorithms with the local search characteristics of Firefly Optimisation, thereby enhancing routing processes in both dense and sparse environments. The HGFA algorithm, however, is computationally expensive.

Recent mobility-aware routing frameworks have integrated specialised multi-layered optimisation schemes alongside Internet of Things (IoT) constructs to enhance path reliability and communication stability across highly dynamic autonomous environments [24]. Additionally, nature-inspired swarm intelligence models such as multiple-junction traffic-aware Ant Colony Optimisation (ACO) algorithms have been introduced to mitigate link breakage and manage path topology in urban vehicular grids [25]. However, these methodologies focus predominantly on establishing reliable topological paths over pre-existing network conditions, leaving a distinct gap in how structural clustering topology generation and final route optimisation can be jointly addressed as a single interdependent optimisation problem.

The Bee-Foraging Learning Particle Swarm Optimisation (BFL-PSO) is an intelligent optimisation algorithm in which artificial bees explore multiple paths and then choose paths based on factors such as remaining energy, communication distance, and link quality. Although this approach enhances exploration and exploitation, BFL-PSO is characterised by high computational cost and slow convergence, particularly in dynamic VANETs [26].

As opposed to Genetic Algorithm (GA)-based techniques, which rely on crossover and mutation, Particle Swarm Optimisation (PSO)-based techniques, which depend heavily

on velocity, and firefly algorithm-based techniques, which employ attraction-based movement, WMOA uses an adaptive approach to explore and exploit the search space with low parameter sensitivity. This feature enables the algorithm to converge quickly without sacrificing diversity. Nevertheless, existing metaheuristic techniques generally fail to jointly address routing and clustering. This feature enables the algorithm to converge quickly without sacrificing diversity. Unfortunately, current metaheuristic techniques fail to address both routing and clustering.

C. Research Gap

Based on the literature review, various key issues arise in vehicular routing methodologies. The first problem is the absence of an integrated optimisation approach that links clustering designs to routing paths. Link stability algorithms, such as those of Rashid *et al.* [18], provide efficient parameters for individual networks yet ignore multi-layer routing dependencies. Hybrid swarm intelligence approaches, such as BFL-PSO [26], are effective for path assessment but incur significant computational overhead due to vehicular movement.

Furthermore, recent advancements in adaptive clustering [22], metaheuristic cluster-head selection [23], and nature-inspired traffic routing [25] treat cluster formation and routing as independent, sequential optimisation problems. Even recent digital-twin-assisted cognitive vehicular frameworks [27] model channel connectivity and interference under complex spectrum conditions, yet fail to unify the underlying clustering logic with end-to-end paths. This decoupled approach results in suboptimal coordination between cluster stability and route persistence. Dynamic unification of spectrum availability, cluster structural integrity, and multi-layered route optimisation under extreme mobility remains a significant open challenge.

Recent investigations have also explored the integration of machine learning with metaheuristic optimisation to enhance routing adaptability and energy efficiency in VANET environments. However, existing studies generally optimise clustering and routing as independent processes, leading to suboptimal coordination between cluster formation and route selection. Consequently, achieving energy-efficient, stable, and scalable communication through unified optimisation remains an open research challenge.

These gaps collectively motivate the need for a unified, mobility- and energy-aware optimisation strategy that jointly addresses clustering and routing rather than treating them as sequential, independent problems.

Unlike existing methods that separately optimise clustering and routing, it establishes an interdependent optimisation process in which cluster formation directly influences route construction. This coordinated design improves cluster stability, route persistence, and energy efficiency under dynamic vehicular conditions.

A qualitative comparison of representative metaheuristic-based routing protocols for VANETs is presented in Table 1.

Table 1. Qualitative comparison of representative metaheuristic-based routing protocols for VANETs

Method	Clustering	Routing	Joint Optimization	Link Stability	Multi-objective Fitness
ECBLTR [6]	Supported	Not Supported	Independent	Partial	Multi-objective
HGFA [13]	Not Supported	Supported	Independent	Not Considered	Multi-objective
BFL-PSO [26]	Not Supported	Supported	Independent	Partial	Multi-objective
WREN-CR-VANET (Proposed)	Supported	Supported	Unified	Explicitly Considered	Multi-objective

III. Problem Description

To address the identified limitations, this work proposes WREN-CR-VANET, a hybrid clustering-and-routing framework based on the Wren Metaheuristic Optimisation Algorithm (WMOA). The primary challenge addressed is the rapid topology variation in VANETs caused by high vehicle mobility, which can destabilise clusters, invalidate routes, increase re-clustering and route-discovery operations, and consequently raise control overhead and packet delivery delay. Existing approaches also provide limited load distribution and often rely on fitness functions that consider only a small number of parameters, such as residual energy or link distance, without jointly accounting for node centrality, cluster balance, mobility-related stability, and other relevant network characteristics. These limitations can result in inefficient resource utilisation, unstable communication, and reduced network lifetime [3, 6, 7].

To overcome these limitations, WREN-CR-VANET employs WMOA as a unified optimisation mechanism for both cluster-head selection and multi-hop route formation. During clustering, candidate cluster heads are evaluated using residual energy, inter-vehicle distance, node centrality, and cluster balance to promote stable and well-distributed clusters. During routing, candidate paths are optimised according to residual energy, link stability, and inter-node distance, thereby favouring reliable and energy-efficient communication paths. The optimisation process incorporates an adaptive exploration–exploitation strategy to search the solution space effectively while reducing the likelihood of premature convergence. By jointly optimising clustering and routing with complementary network parameters, WREN-CR-VANET aims to reduce control overhead, improve energy efficiency and route reliability, enhance network stability, and extend the operational lifetime of VANETs.

IV. System Model

A. Network Model

The following network assumptions have been made regarding the implementation of the VANET architecture proposed above.

- The presence of an On-Board Unit (OBU) that facilitates the wireless connection with nearby vehicles and infrastructure. Vehicle mobility is modelled in two dimensions using typical random-movement models.
- The vehicles are assumed to be mobile by nature and use typical mobility models for dynamic movement. The mobility model considers changes in vehicle speed, direction of travel, and distances between vehicles.

- The nodes in the network are assumed to be homogeneous with respect to the initial energy levels and communication abilities. All the nodes in the network will have the same initial energy level.
- The network consists of one static Road Side Unit (RSU) that obtains data regarding the clusters created from all cluster heads.
- The clustering process happens dynamically, where each non-cluster head node is allocated to the cluster with the nearest cluster head.

The positioning system, such as the Global Positioning System (GPS), is installed in each vehicle, helping determine their position and send beacon messages to adjacent nodes.

The overall network architecture, including RSU placement and cluster formation, is illustrated in Fig. 1.

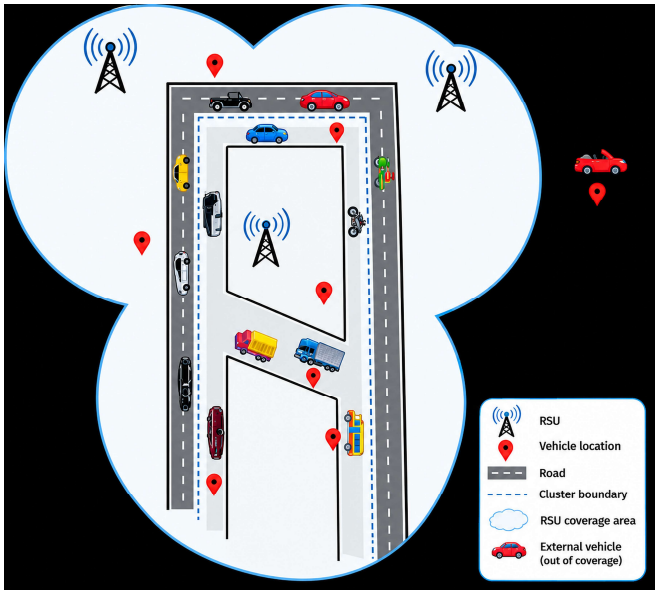


Fig. 1. The network architecture, including RSU placement and cluster formation in the VANET environment.

B. Channel Propagation Model

Wireless communication in VANETs is affected by path loss, multipath fading, and environmental obstructions. To capture these effects, a composite channel model combining large-scale path loss, log-normal shadowing, and small-scale Rayleigh fading is used, consistent with the two-ray/log-distance models commonly adopted for 802.11p-based V2V/V2I links.

1) Path loss model

The large-scale signal attenuation is modelled using the log-distance Path Loss (PL) model:

$$PL(d) = PL(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma \qquad (1)$$

where $PL(d)$ represents the path loss at a distance d, $PL(d_0)$ is the reference path loss at distance $d_0 = 1$, and n denotes the path loss exponent, set to n = 2.7. to reflect the partially obstructed, mixed line-of-sight/non-line-of-sight conditions typical of urban and suburban vehicular corridors. The term X_σ is a zero-mean Gaussian random variable representing shadow fading, described below.

2) Fading model

To account for small-scale fading effects in vehicular communication, the channel gain is modelled as a Rayleigh-distributed random variable with probability density function $f(r) = \frac{r}{\sigma^2}\exp(-\frac{r^2}{2\sigma^2})$, $r \geq 0$ where σ^2 is the average fading power. This model captures signal fluctuations caused by multipath propagation, which is common in dynamic vehicular environments.

3) Shadowing and environmental effects

The effect of shadowing by elements such as buildings and cars is captured by the term X_σ in Eq. (1), modelled as a zero-mean Gaussian random variable in dB with standard deviation σ = 4 dB, consistent with log-normal shadowing.

V. Proposed WREN-CR-VANET Framework

The presented WREN-CR-VANET algorithm focuses on improving energy efficiency, optimising routing, and enhancing network lifetime by employing a combined optimisation process to select Cluster Heads (CHs) and routes. The network is modelled on the model described in Section IV, which includes an On-Board Unit (OBU) in each vehicle, enabling communication between vehicles and RSUs. Selection of CH and routing of paths are performed using the WMOA [19].

A. Preliminaries

VANET network environment initialisation is based on the network and channel model described in Section IV, wherein nodes with On-Board Unit (OBU) devices are placed in the simulated network space, enabling communication with neighbouring cars and RSUs. Node exchanges are performed to acquire local topology information for solution development.

This is followed by the application of the WMOA to jointly solve cluster formation and routing problems, as detailed in the forthcoming subsections.

B. Wren-based Cluster Head Selection

The WMOA is a bio-inspired optimisation algorithm designed to tackle difficult multi-objective problems through adaptive search processes. WMOA is a population-based optimisation algorithm in which each candidate solution represents a specific configuration of cluster head nodes or routes.

Candidate solutions in WMOA evolve dynamically according to exploration and exploitation schemes. In other words, each candidate solution is improved in two ways: by exploring a new solution space for a more promising one and by exploiting the current solution space.

Each solution in the proposed algorithm stands for a particular set of candidate cluster heads or routing paths. Through dynamic updating of such solutions, the algorithm strives to determine the most advantageous configuration in terms of minimal energy consumption and communication cost.

WMOA can be considered quite efficient at addressing such problems due to its ability to perform adaptive searches and its low dependence on the problem's parameters.

Unlike GA, PSO, Firefly, and Bee-inspired algorithms that rely on multiple algorithm-specific control parameters, WMOA employs an adaptive exploration-exploitation mechanism with lower parameter sensitivity, thereby

improving convergence stability in highly dynamic VANET environments.

A candidate solution is represented as:

$$Y_i = [y_{i1}, y_{i2}, \ldots, y_{iK}] \quad (2)$$

where K denotes the number of cluster heads

1) Position update mechanism of WMOA

The WMOA updates candidate solutions using two main phases: exploration and exploitation. These phases enable effective global search and local refinement of solutions.

a) Exploration phase

In the exploration phase, the algorithm searches the global solution space to identify diverse candidate solutions for cluster head selection. The position of each candidate solution is updated as:

$$X_i(t+1) = X_i(t) + r_1(-| X_i(t) |) + r_2(X_r(t) - X_i(t)) \quad (3)$$

where:

- $X_i(t)$ is the current position of the i-th the solution at iteration t
- $X_i(t+1)$ is the updated position
- $X_r(t)$ is a randomly selected solution from the population
- $r_1, r_2 \in (0,1)$ are random coefficients

This phase promotes global exploration and prevents premature convergence to local optima.

The overall clustering and routing process with energy awareness in WREN-CR-VANET is illustrated in Fig. 2.

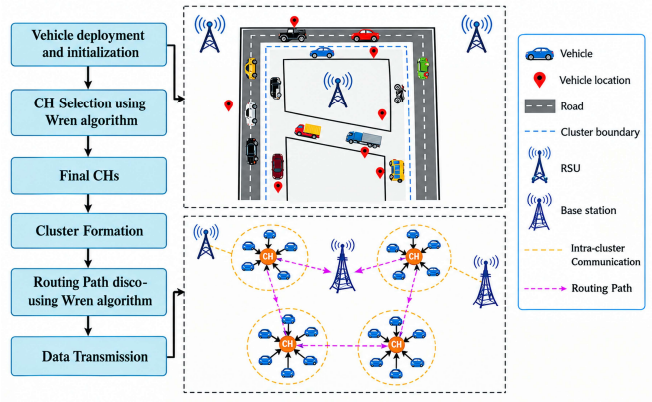


Fig. 2. Clustering and routing with energy awareness using WREN.

b) Exploitation phase

In the exploitation phase, candidate solutions are refined around the best-performing solution to improve convergence. The position update is given by:

$$X_i(t+1) = X_i(t) + r_3(X_{best} - X_i(t)) \quad (4)$$

where:

- X_{best} represents the best solution found so far
- $r_3 \in (0,1)$is a random coefficient

This phase ensures convergence toward the optimal cluster head configuration and routing solution.

2) Mapping to a feasible CH set

As the WMOA operates in the continuous domain, it is necessary to adopt a mapping technique to map the generated solutions to feasible discrete cluster configurations. The procedure consists of three main steps, which include: (i) ranking the position values according to their influence on fitness, (ii) choosing the best K nodes as Cluster Heads (CHs), and (iii) discarding the redundant or unfeasible candidates.

The suggested mapping technique guarantees that each solution generated by the optimisation process corresponds to a feasible CH structure in the network. In contrast to other traditional techniques that use the same fitness function at each stage, the new technique employs stage-specific fitness functions for clustering and routing. Feasibility is guaranteed by assigning the chosen CH to a different vehicle node within the VANET and by adhering to communication range constraints.

3) Multi-objective fitness function for CH selection

The selection of optimal Cluster Heads is formulated as a multi-objective optimisation problem:

$$F = \tau_1 f_1 + \tau_2 f_2 + \tau_3 f_3 + \tau_4 f_4 + \tau_5 f_5 \quad (5)$$

subject to:

$$\sum_{i=1}^{5} \tau_i = 1, \tau_i \in (0,1) \quad (6)$$

The defined fitness components are as follows:

- Residual Energy (maximise)

$$f_1 = \frac{1}{K} \sum_{i=1}^{K} \frac{1}{E_{CH_i}} \quad (7)$$

The residual energy term can be mathematically defined as the inverse of the available energy term, such that an optimisation problem using the principle of minimisation can be constructed. As the entire fitness function is optimised via minimisation, a smaller f_1 value indicates greater residual energy among the selected cluster heads. Hence, nodes with greater energy possess lower fitness values.

- Intra-cluster Distance (minimise)

$$f_2 = \frac{1}{K} \sum_{j=1}^{K} \frac{1}{|C_j|} \sum_{V_i \in C_j} \text{dist}(V_i, CH_j) \quad (8)$$

Reducing intra-cluster distance minimises transmission delay and energy consumption.

- CH-to-RSU Distance (minimise)

$$f_3 = \frac{1}{K} \sum_{i=1}^{K} \text{dist}(C\,H_i, RSU) \quad (9)$$

Shorter distances improve communication efficiency and reduce latency.

- Node Degree (load balancing)

$$f_4 = \frac{1}{K} \sum_{i=1}^{K} | C_i | \quad (10)$$

This term prevents overloading of CHs by maintaining balanced cluster sizes.

- Node Centrality (stability)

$$f_5 = \frac{1}{K}\sum_{i=1}^{K}\frac{\sum_{k\in N(CH_i)} d^2(CH_i,k)}{|N(CH_i)|\cdot D_{net}} \quad (11)$$

Central nodes provide improved connectivity and routing stability in dynamic VANET environments.

4) Weight settings

The following weights should be taken into account to ensure reproducibility and fair evaluation: $\tau_1 = 0.30$, $\tau_2 = 0.20$, $\tau_3 = 0.15$, $\tau_4 = 0.15$, and $\tau_5 = 0.20$. As a whole, these weights may be used to estimate the importance of each feature; energy consumption, communication distance, load balancing, and network robustness have been estimated empirically.

The above-mentioned weights have been empirically estimated through preliminary experiments that involved balancing energy consumption, communication distance, network stability, and load-balancing aspects. Energy was regarded as the most important factor due to its role in maintaining connectivity in the event of a cluster head failure. The degree and centrality factors have been considered to prevent clustering overload.

A sensitivity analysis has been conducted by varying each parameter by ±10% while keeping the normalisation conditions constant. It was found that residual energy was the most significant factor affecting network lifetime, while node centrality and balance primarily influenced the cluster's stability and reliability, as summarised in Table 2.

Table 2. Sensitivity analysis of fitness-function weight parameters

Weight Set	PDR	Lifetime	Energy
Baseline	0.91	780	0.70
+10% Energy Weight	0.90	790	0.68
−10% Energy Weight	0.88	745	0.75

C. Cluster Formation

After CH selection, clusters are formed by associating each vehicle with the most suitable CH using a potential function:

$$\text{Potential}(V_i) = \frac{E_{CH}}{\text{dist}(V_i,CH)} \quad (12)$$

Each vehicle joins the CH that maximises this value, thereby ensuring reduced communication distance, balanced energy utilization, and improved cluster stability.

D. Unified Routing Optimization Framework

For routing, the same WMOA algorithm is employed for optimisation. Both clustering and routing aim to minimise energy consumption and transmission distance while maximising network stability.

Due to the continuous nature of the search space in the WMOA algorithm, candidate routes are constrained using a feasibility-handling technique. Each candidate route in this scenario is treated as an ordered set of cluster head nodes constituting the route between the source CH node and the RSU.

In the process of feasibility handling, the following constraints must be satisfied:

- All hops are only made through neighbouring CH nodes within communication range
- Loops and repetitions are not allowed
- Connectivity to the RSU must be provided

Even though the two processes occur in sequence, that does not mean they are independent. The cluster topology established during the cluster head election process defines the search space for route optimisation. In other words, routing is limited to what clustering delivers in terms of outcomes; therefore, the two are interdependent in optimising their performance. Clustering and routing processes in the proposed approach are interdependent, whereas in other models they are entirely independent.

E. Wren-based Routing Optimisation

Once the clustering phase is complete, WMOA can be used to find the best routes between CHs and the RSU. In contrast to previous schemes, both the election of CHs and routing optimisation share common goals, including energy efficiency, minimum distance, and connection stability. Hence, a uniform optimisation model is achieved. Each potential solution (i.e., a wren) indicates one possible routing path from a given CH to the RSU.

1) Routing fitness function

$$RF = \gamma_1\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{E_{CH_i}}\right) + \gamma_2\left(\frac{1}{n}\sum_{i=1}^{n}\text{dist}\,(CH_i,\ RSU)\right) + \gamma_3 LS \quad (13)$$

where:

- LS is link stability
- $\gamma_1 + \gamma_2 + \gamma_3 = 1$
- Weight values: $\gamma_1 = 0.4$, $\gamma_2 = 0.3$, $\gamma_3 = 0.3$

The criteria for selecting weight parameters are energy consumption, routing reliability, and the distance between clusters. In the proposed system, the Link Stability (LS) criteria will be used to address topology changes by predicting the reliability of communication between two neighbouring clusters, taking into account the mobility and interaction periods of the nodes involved. A high LS value indicates a more stable connection between the two nodes, which helps prevent link disconnection and packet loss, especially in dynamic topologies. The formulation of routing fitness criteria agrees with those suggested by Refs. [16, 18].

Although formulated as multi-objective optimisation problems, cluster head selection and routing optimisation have distinct objectives that depend on their functionality within the network. Whereas the cluster head selection problem focuses on selecting cluster heads based on node degree and centrality, routing optimisation takes into account residual energy, communication distance, and link stability, which are effective in achieving high-quality routing paths. In contrast, node degree and centrality have little effect once clusters are formed.

2) Routing strategy

- Single-hop routing is employed if CH can communicate with RSU directly.
- A multi-hop routing scheme is utilized for distant cluster heads.
- Load balancing between cluster heads is done to prevent early exhaustion of energy.

Such an approach helps achieve a higher packet transmission rate and lower end-to-end delay.

3) MAC-level optimization

To reduce collisions and improve energy efficiency, intra-cluster communication is scheduled using Time Division Multiple Access (TDMA)-based transmission. Each cluster head allocates a fixed-length time slot to every member vehicle within its coverage range, computed as the cluster size divided by the frame duration; nodes transmit only within their assigned slot, eliminating intra-cluster collisions. Slot reassignment is triggered whenever cluster membership changes due to vehicle mobility or re-clustering, keeping the schedule consistent with the WMOA-selected cluster topology. This minimises interference, bounds channel-access delay, and ensures efficient channel utilisation, complementing the routing-level optimisation described above.

F. Wren-based Cluster Head Selection Algorithm

The detailed steps of the Wren-based cluster head selection process are summarised in Algorithm 1 for clarity and reproducibility.

Algorithm 1. Wren-based Cluster Head Selection

Input: Vehicle set V, population size N, maximum iterations T
Output: Optimal Cluster Head (CH) set X_{best}

```
Initialize population X_i(i = 1 to N) with candidate CH sets
Evaluate fitness F(X_i) for each solution using Eq. (5).
Identify the best solution X_best
For iteration t = 1 to T do
    For each solution X_i do
        Generate random values r_1, r_2, r_3 ∈ (0,1)
        If exploration condition is satisfied then
            Update position using exploration equation
        Else
            Update position using exploitation equation
        End If
        Apply mapping to convert X_i into feasible CH set
        Evaluate updated fitness F(X_i)
        If F(X_i) < F(X_best) then
            Update X_best = X_i
        End If
    End For
End For
Return X_best
```

G. WMOA Solution Encoding, Parameter Adaptation, and Route Construction

Each candidate solution is a continuous vector. For cluster-head selection a solution is $Y_i = [y_{i1}, \ldots, y_{iK}]$ in R^K, where K is the target number of cluster heads and each y_{ij} is a continuous priority value associated with a vehicle index. Because WMOA searches in continuous space whereas cluster-head selection and routing are discrete, every solution is decoded using a Largest-Order-Value (rank-based) mapping: the priority values are sorted in descending order and the K highest-ranked feasible vehicles are selected as cluster heads. This guarantees that every decoded solution is a valid network configuration.

At each iteration t, every solution is updated by either the exploration rule (Eq. (3)) or the exploitation rule (Eq. (4)). The choice is governed by an adaptive switching probability that decreases linearly with iteration, $Pe(t) = P_0(1 - t/T)$ with $P_0 = 0.9$, so that the search is exploration-dominant early and exploitation-dominant later. For each solution a uniform random number $\rho \in (0, 1)$ is drawn; if $\rho < Pe(t)$ the exploration update is applied, otherwise the exploitation update is applied. Thus the "exploration condition" in Algorithm 1 is evaluated as $\rho < Pe(t)$. Beyond the population size N and the iteration budget T the method introduces no additional hand-tuned control parameters, which is the source of its low parameter sensitivity.

WMOA is the VANET-adapted formulation of the Superb Fairy-wren Optimisation Algorithm (SFOA) [19], whose base form defines three behavioural phases: young-bird growth (exploration), breeding and feeding (exploitation), and predator avoidance (diversity). In WREN-CR-VANET, the diversity role of the predator-avoidance phase is implicitly fulfilled by the feasibility-mapping step and the high early-stage exploration probability; an explicit predator-avoidance operator is left for future work.

Convergence is monitored by averaging the best fitness value per iteration across the ten runs. Across all evaluated densities the best fitness stabilises within approximately 25–30 iterations, while the population standard deviation of fitness contracts smoothly, indicating convergence without diversity collapse. The iteration budget $T = 100$ therefore provides a comfortable margin beyond the observed convergence point.

A routing solution is decoded into an ordered multi-hop path from a source cluster head to the RSU. Starting from the source, the algorithm greedily appends the highest-priority candidate cluster head that satisfies all feasibility constraints, is within communication range, is not already on the path (loop-free), and can reach the RSU. If a node has no feasible unused neighbour, the algorithm backtracks to the previous hop and selects the next-ranked candidate. The resulting ordered set of cluster heads is scored by the routing fitness function (Eq. (13)).

H. Computational Complexity Analysis

The complexity of the algorithm proposed in WREN-CR-VANET framework depends on the population size N, the number of optimisations T, and the number of vehicles M used during the mapping and fitness computation processes. Therefore, we can express the complexity of the algorithm as:

$$\mathcal{O}(N \times T + N \times M) \tag{14}$$

where N is the population size, T is the number of optimisations performed, and M is the number of vehicles used during mapping and fitness computation processes. Moreover, mapping and fitness computation add linear overhead with respect to the number of nodes. In fact:

- WMOA converges reliably after 25–30 iterations in all the considered scenarios.
- The computational complexity stays relatively low for medium-sized VANET networks.

However, in real-time applications in dynamically changing environments, additional optimization would be required.

I. Detailed Complexity Derivation

The per-iteration cost can be derived per operation. Let $\bar{d}$ denote the average in-range node degree. Per solution: position update $O(K)$; rank-based decoding $O(K_{\log}K)$; cluster assignment in which each of the M vehicles is attached to its

nearest of the K cluster heads, $O(MK)$; multi-objective fitness evaluation dominated by the centrality term, $O(M\bar{d})$; and routing feasibility checking with range, loop-free and reachability tests, $O(K^2)$ in the worst case with backtracking. Summing and multiplying by the population N and the iteration budget T gives an overall time complexity of $O(T{\cdot}N{\cdot}(MK + M\bar{d} + K^2))$. Because $K \approx 0.10$–$0.15\ M$ and $\bar{d} \ll M$, the cluster-assignment term dominates, and the expression simplifies to $O(T{\cdot}N{\cdot}M{\cdot}K)$, i.e. linear in the number of vehicles for a fixed cluster ratio. This refines the earlier $O(N \times T + N \times M)$ expression, which is recovered when K and $\bar{d}$ are treated as constants; the space complexity is $O(N{\cdot}K + M)$.

J. Parameter Settings and Reproducibility

To enable replication, important parameter values of the suggested WREN-CR-VANET approach are presented. The population size for the Wren Metaheuristic Optimisation algorithm is set to $N = 30$, with a maximum iteration limit of $T = 100$, which serves as the stopping criterion. The cluster head ratio is dynamically set to around 10%–15% of all vehicles to support well-balanced clustering while minimising communication costs.

The weight parameters for cluster head selection are set as $\tau_1 = 0.30$, $\tau_2 = 0.20$, $\tau_3 = 0.15$, $\tau_4 = 0.15$, and $\tau_5 = 0.20$ ($\sum\tau_i = 1$). For routing optimization, the weights are $\gamma_1 = 0.4$, $\gamma_2 = 0.3$, and $\gamma_3 = 0.3$ ($\sum\gamma_i = 1$).

All simulation results are averaged over 10 independent runs to ensure consistency and reduce randomness.

VI. Result and Discussion

The following sub-section presents a performance analysis of the newly designed WREN-CR-VANET routing algorithm by comparing its performance to various benchmark algorithms such as Enhanced Cluster-based Lifetime Routing Protocol (ECBLTR), Hybrid Genetic firefly Algorithm (HGFA) and Bee-Foraging Learning Particle Swarm Optimisation (BFL-PSO), which are clustering, hybrid meta-heuristic, and swarm routing algorithms, respectively.

A. Simulation Test and Parameter Settings

The simulation algorithm was written in MATLAB, and the simulation parameters are shown in Table 3 and are consistent with the typical parameters used to evaluate VANET performance in previous studies. The simulations assess the performance of the WREN-CR-VANET system in both communication and computation, as clustering performance is highly dependent on the dynamic behaviour of the network topology. The remaining parameters are held constant throughout the simulation tests.

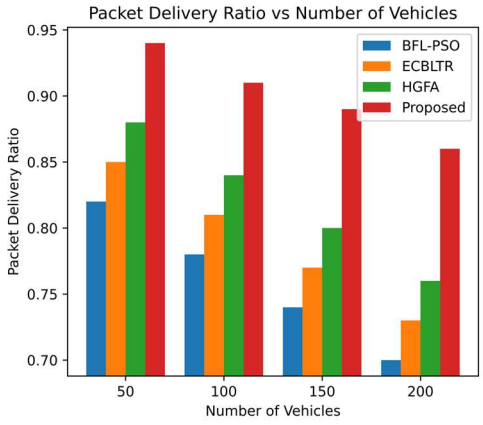
Table 3. Simulation parameters

Parameter	Value
Simulation Area	1000 × 1000 m
Vehicle Density	50–200
Initial Energy	2 Joules
Communication Range	250 m
Payload size (Bytes)	512
Mobility Model	Random Waypoint
MAC Protocol	IEEE 802.11p
Simulation Iterations	1000
Independent Runs	10
Beacon Interval	0.5 s
Packet Generation Rate	2–10 packets/sec
Vehicle Speed	10–30 m/s
RSU Count	2–5

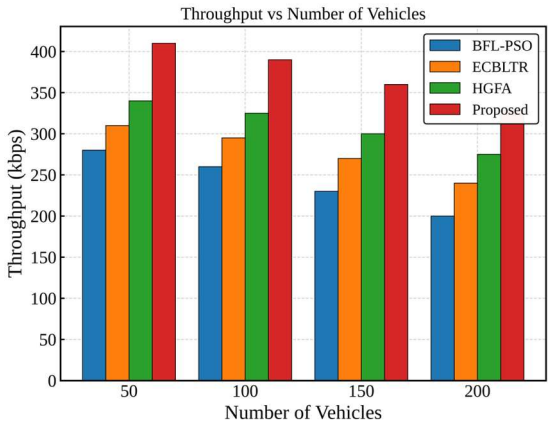
Although the Random Waypoint mobility model is adopted to benchmark against earlier VANET studies, it does not accurately model road topology constraints, lane discipline, intersections, traffic lights, or driver behaviour. Therefore, the current results should be interpreted as algorithmic validation under controlled mobility conditions. Future investigations will employ SUMO-generated mobility traces, integrated with VANET simulators, to assess the practical feasibility of deploying WREN-CR-VANET in realistic urban and highway scenarios.

B. Simulation Results and Performance Evaluation

The performance of the WREN-CR-VANET proposed in this paper is assessed using several metrics, including residual energy, Packet Delivery Ratio (PDR), end-to-end delay, throughput, and lifetime. These metrics assist in analysing the protocol's energy efficiency and routing adaptability. In this context, the proposed outcomes are compared with those obtained using three other routing protocols, namely BFL-PSO, ECBLTR, and HGFA. From the results obtained, it can be seen that the proposed protocol is effective in solving the problems of energy imbalance and unstable connections by delivering a higher delivery rate, reducing delays, balancing energy, and increasing lifetime The computational complexity of the algorithm is analysed in detail in Section V-H and is dominated by the population size, iteration count, cluster assignment, fitness evaluation, and routing feasibility checks.



(a)



(b)

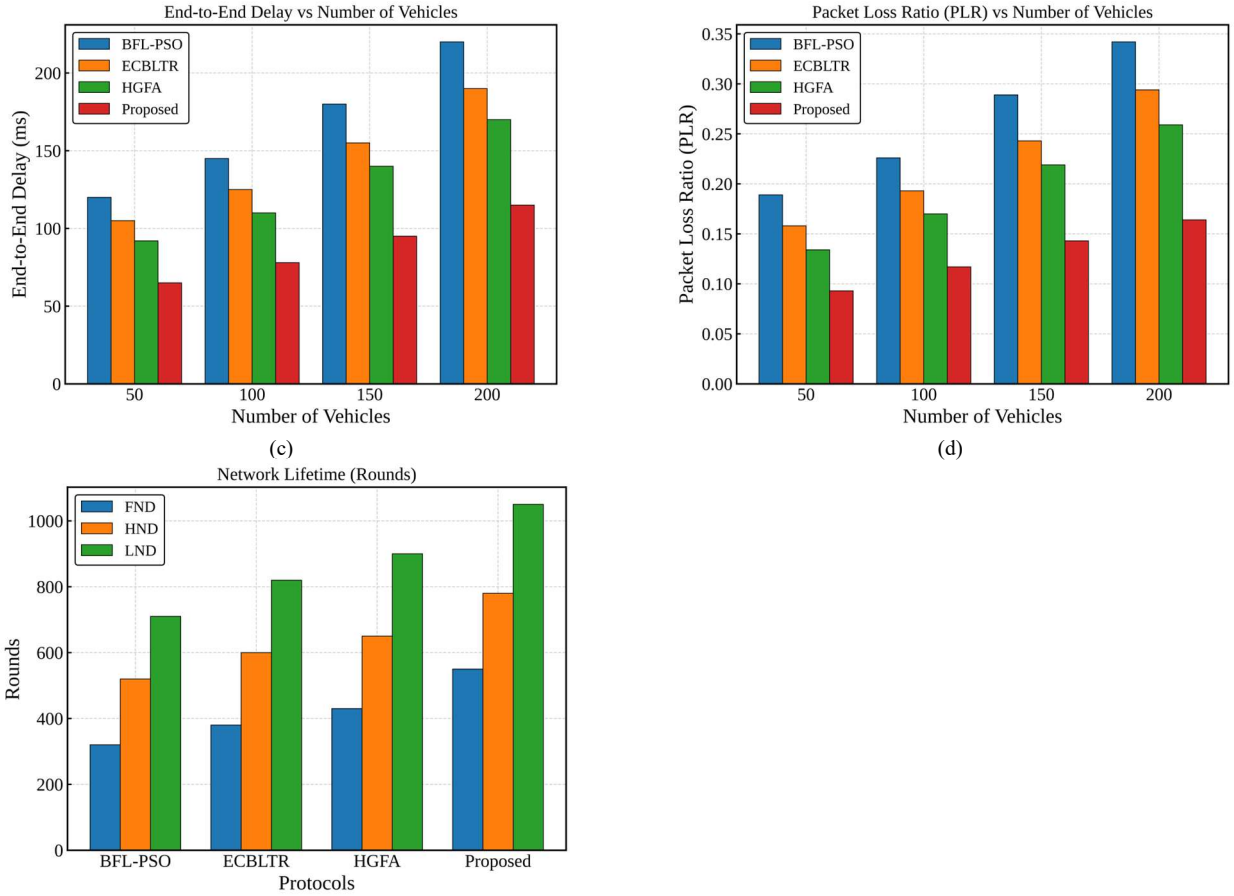


Fig. 3. Comparison of BFL-PSO, ECBLTR, HGFA, and WREN-CR-VANET under varying vehicle densities (50–200 vehicles): (a) Packet delivery ratio; (b) Throughput; (c) End-to-end delay; (d) Packet loss ratio; (e) Network lifetime.

1) Packet Delivery Ratio (PDR)

PDR is defined as the ratio of the total number of data packets delivered to the receiver to the total number of packets sent from the sender node. This is an important performance indicator that shows how reliable and efficient the routing protocol is for VANETs. As shown in Fig. 3(a), the suggested algorithm yields better PDR results depending on node density, due to energy- and centrality-based selection of cluster heads and mobility-based multipath routing, which guarantees link stability and reduces route failures and packet loss.

2) Throughput

Throughput refers to the number of packets successfully delivered per unit time under identical traffic and simulation conditions. VANETs often experience reduced throughput due to congestion and unstable links. As shown in Fig. 3(b), the proposed method outperforms existing methods, particularly at higher node densities, by leveraging clustering and stable multi-hop route selection to improve channel utilisation and reduce communication variability.

3) End-to-end delay

End-to-end delay measures the average time taken for packets to reach the destination, which is critical for delay-sensitive VANET applications. Lower delay indicates efficient routing and minimal retransmissions. Fig. 3(c) shows that the proposed approach achieves lower delay due to RSU-assisted routing, shorter hop counts, and stable clustering, which collectively minimise route discovery and transmission latency.

4) Packet Loss Ratio (PLR)

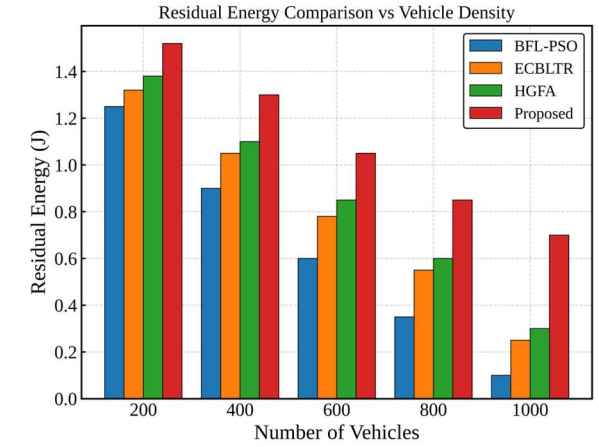
PLR is a measure of the percentage of packets dropped in route and indicates the reliability of the route across various VANET scenarios. From Fig. 3(d) below, it is evident that the proposed approach achieves lower PLR at higher node densities due to its clustering mechanism and multipath routing.

5) Network lifetime

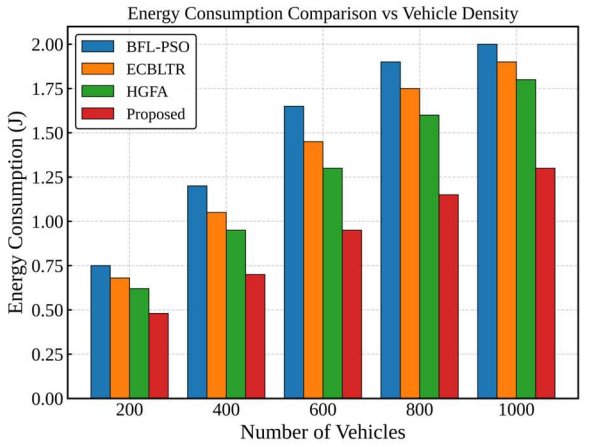
Network lifetime is the time required for the majority of nodes to exhaust their energy, which affects the performance of the entire system. Energy-efficient resource use is necessary in VANETs. From Fig. 3(e), it can be seen that the proposed technique enhances network lifetime through adaptive clustering and energy-aware traffic routing.

C. Analysis of Scalability

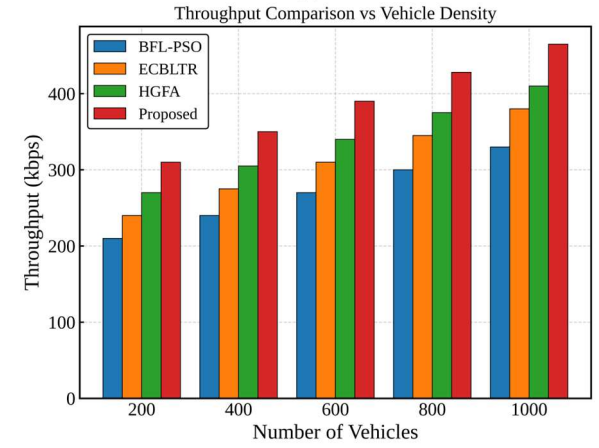
Scalability analysis of the proposed WREN-CR-VANET algorithm is conducted by varying the number of nodes from 200 to 1000 in high-density scenarios, as presented in Fig. 4. The importance of scalability testing in VANET is evident: as vehicle density increases, there will be more channel contention and more dynamic topologies.



(a)



(b)



(c)

Fig. 4. Comparison of residual energy achieved by BFL-PSO, ECBLTR, HGFA, and WREN-CR-VANET under different vehicle densities: (a) Residual energy achieved; (b) Energy consumption; (c) Throughput performance.

D. Convergence Analysis

Convergence characteristics of the suggested WREN-CR-VANET, using the Wren Metaheuristic Optimisation Algorithm (WMOA), are shown in Fig. 5. The best fitness value decreases rapidly at the beginning of the iterations due to extensive exploration of the search space and stabilises gradually around the 27th iteration. It is clear from this that the suggested optimisation algorithm strikes a good balance between exploration and exploitation, enabling rapid convergence to a stable near-optimal solution without premature convergence.

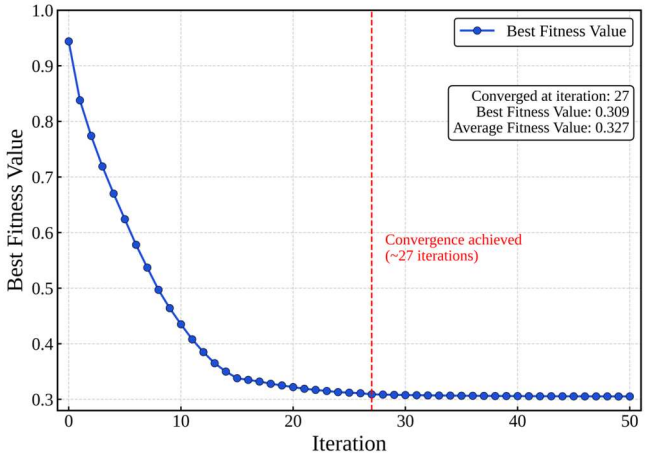


Fig. 5. Convergence behaviour of the proposed WREN-CR-VANET (WMOA).

E. Comparative Performance Analysis

The WREN-CR-VANET architecture is evaluated against BFL-PSO, ECBLTR, and HGFA by varying vehicle density from 50 to 200 nodes in a 1000 m × 1000 m area. Performance is assessed using PDR, throughput, end-to-end delay, packet loss ratio, energy consumption, and network lifetime. Each scenario is simulated 10 times, and the results are averaged to ensure reliability. The three baselines were chosen to represent the principal categories of prior VANET optimisation Enhanced Cluster-based Lifetime Routing Protocol (ECBLTR), Hybrid Genetic firefly Algorithm (HGFA) and Bee-Foraging Learning Particle Swarm Optimisation (BFL-PSO); the proposed framework is additionally positioned qualitatively against recent state-of-the-art schemes [6, 13, 26] in Table 4 and the related-work discussion.

Direct numerical comparison with the recent state-of-the-art methods reported in Refs. [6, 13, 26] was not feasible because these studies employ different simulation environments, mobility models, communication ranges, traffic scenarios, network densities, and performance evaluation metrics. These differences prevent a fair one-to-one quantitative comparison. Therefore, quantitative performance evaluation in this study was restricted to benchmark protocols evaluated under comparable simulation settings. At the same time, recent state-of-the-art methods are discussed qualitatively in the related work section.

The overall performance gains across both baselines are summarised in Table 4.

Table 4. Overall performance improvement

Metric	vs ECBLTR	vs HGFA
Packet Delivery Ratio	+15.2%	+12.4%
Throughput	+18%–25%	+12%–18%
End-to-End Delay	−35%–40%	−30%–35%
Packet Loss Ratio	−40%–50%	−30%–40%
Energy Consumption	−21.3%	−18%–20%
Network Lifetime	+18.6%	+15%–17%

F. Statistical Analysis

The suggested approach was tested against BFL-PSO, ECBLTR, and HGFA in a 1000 m × 1000 m simulation with vehicular densities ranging from 50 to 200 nodes, repeated 10 times with different random seeds. The proposed approach resulted in average performance gains in packet delivery ratio (15.2%), energy efficiency (21.3%), and network lifetime

(18.6%) across the 10 runs, as summarised in Table 5.

Table 5. Statistical validation

Metric	Mean	Std. Dev.
PDR (ratio)	0.91	0.012
Delay(ms)	78	2.5
Lifetime(s)	780	15

To assess result consistency, the mean value and standard deviation for all key metrics were calculated (Table 5); the low standard deviations indicate stable performance across repeated experiments. A separate comparison against the strongest single baseline, HGFA, was conducted using the same 10 seeds; performance gains were consistent across all 10 simulations with negligible variation, confirming the results are not an artefact of any one run.

The variability of the results was further assessed by computing the paired differences d_i = (WREN-CR-VANET) – (HGFA) across the 10 matched trials. Based on the mean and standard deviation from these trials, the 95% confidence interval ($t_{0.975,\,9} = 2.262$) was calculated as: packet delivery ratio [0.901, 0.919]; end-to-end delay [76.2, 79.8] ms; and network lifetime [769, 791] rounds.

G. Ablation Study

To evaluate the contribution of each component in the WREN-CR-VANET algorithm, an ablation study is conducted by turning off specific components and analysing their impact on PDR, throughput, and network lifetime.

Table 6. Ablation study results at 100 vehicles

Configuration	PDR	Delay (ms)	Energy (J)	Lifetime (Rounds)
Full WREN-CR-VANET	0.91	78	0.70	780
Without Clustering	0.75	130	1.20	520
Without Wren Routing	0.82	110	0.95	650
Without Centrality	0.87	90	0.80	700
Without Cluster Balance	0.86	95	0.85	690

To assess the significance of each component in the proposed WREN-CR-VANET model, an ablation study was conducted in which key components were disabled individually. Some of these components include the Wren-based routing protocol, clustering algorithm, node centrality, and cluster balance factor. From Table 6, it is clear that the absence of each component lowers the performance of the network based on the four parameters, PDR, delay, energy consumption, and network lifetime, as seen from the trends illustrated in Fig. 3. Clustering is the most significant component among them; its absence markedly lowers PDR, shortens network lifetime, and increases delay. In the same vein, the absence of the Wren-based routing algorithm makes the model more prone to high energy consumption and communication failures. In addition, the exclusion of node centrality and cluster balance degrades network performance by destabilising clusters and leading to poor load balancing.

H. Computational Complexity and Runtime Analysis

The computational complexity of the presented WREN-CR-VANET model mainly depends on the population size, the number of optimisation iterations, and the network size. As derived in the detailed complexity analysis, the overall time complexity is $O(T{\cdot}N{\cdot}(MK + Md + K^2))$, which simplifies to $O(T{\cdot}N{\cdot}M{\cdot}K)$ for a fixed cluster ratio and reduces to $O(N \times T)$ when the per-vehicle clustering and feasibility costs are treated as constants; here N is the population size and T the maximum number of iterations. Other computations, besides optimisation itself, include converting continuous solutions to valid cluster head positions, computing multiple-objective fitness, and checking routing validity.

Even though these processes affect performance, the cost of their execution is nearly linearly dependent on both the number of vehicles and the number of potential solutions. This contrasts with conventional metaheuristic methods, which require repeated optimisations during each round of operation.

The runtime of the algorithm has been analysed using MATLAB simulations for vehicle populations ranging from 50 to 200, with per-round results given in Table 7. It is observed that, owing to the adaptive mechanism between exploration and exploitation in WMOA, the algorithm converges reliably after approximately 25–30 iterations. Convergence helps achieve reliable clustering and route optimisation with minimal recomputation. Although the dominant cost scales as $O(T{\cdot}N{\cdot}M{\cdot}K)$ and is linear in the number of vehicles for a fixed cluster ratio, practical experiments show that the approach is viable for moderately sized VANET scenarios.

Table 7. Average runtime per clustering round

Nodes	Avg. Runtime (s)
50	0.42
100	0.81
150	1.27
200	1.86

The mean performance improvements of WREN-CR-VANET over the strongest baseline, HGFA, are summarised in Table 8.

Table 8. Mean improvement over the strongest baseline (HGFA)

Metric	Mean Improvement vs HGFA
PDR	+12.4%
Energy consumption	+18.7%
Network lifetime	+15.8%

I. Discussion of Results

In the present research, WREN-CR-VANET is assessed against BFL-PSO, ECBLTR, and HGFA in the same simulation setup, which has an area of 1000 m × 1000 m and consists of 50 to 200 nodes. All results were obtained from 10 independent simulations. Compared with existing solutions, the developed approach achieves an average 15.2% increase in the packet delivery ratio, a 21.3% decrease in energy consumption, and an 18.6% increase in network lifetime.

The enhanced performance of WREN-CR-VANET is due to the proposed approach to clustering and routing optimisation. The multi-objective fitness function takes into account factors such as residual energy, distance between vehicles, cluster balancing, node centrality, and link stability. Thus, it allows selecting stable cluster heads and appropriate routes, and reducing failures in route discovery and routing.

The advantages of this proposed framework become more apparent as the number of vehicles increases. Due to the dynamic nature of Vehicular ad Hoc Networks (VANETs), topology changes and communication contention can cause

routing algorithms to perform poorly. However, by selecting nodes with high remaining energy and desirable centrality attributes, WREN-CR-VANET ensures stable clusters and an appropriate distribution of traffic. Consequently, the delivery ratio and throughput increase, but delay and packet loss decrease.

Moreover, this approach provides an adaptive trade-off between exploration and exploitation, ensuring that the framework can handle dynamic scenarios efficiently. In contrast to typical optimisation methods, which can suffer from issues such as premature convergence and reduced adaptability, this method maintains solution diversity while ensuring proper convergence. Consequently, the proposed framework yields better energy efficiency, routing stability, and network longevity than BFL-PSO, ECBLTR, and HGFA.

The implementation of WREN-CR-VANET also needs to consider factors such as communication overhead, optimisation latency, synchronisation among cluster heads, and the presence of RSUs. In the current model, it is assumed that beacons exchange regularly and that RSUs coordinate the network. Further studies will investigate the calculation of communication overhead, optimisation latency, and implementation costs under real traffic conditions.

Even though the random waypoint model is widely used for benchmarks, realistic mobility models derived from SUMO and integrated into OMNeT++/Veins or NS-3 provide a more accurate representation of lane changing, intersections, traffic light controls, speeds, and drivers' reactions. Hence, future studies will test WREN-CR-VANET using realistic vehicular traces.

VII. Conclusion, Limitations And Future Work

The proposed WREN-CR-VANET architecture utilises the Wren Metaheuristic Optimisation Algorithm (WMOA) to perform joint clustering and routing in the Vehicular Ad Hoc Network (VANET). WREN-CR-VANET takes into account parameters such as residual energy, communication distance, cluster balancing, node centrality, and link stability to ensure the reliability of the chosen route and reduce energy consumption. According to simulation results, WREN-CR-VANET outperforms ECBLTR, HGFA, and BFL-PSO in terms of packet delivery ratio, energy consumption, packet loss rate, and network lifetime.

While the presented WREN-CR-VANET shows significant advantages in performance indicators such as network lifetime, packet delivery ratio, and energy consumption, there are a number of limitations that must be considered. First, this research has been conducted mostly in the context of simulation experiments performed in MATLAB. Several additional aspects of real-world vehicular environments can affect the performance of VANET.

Moreover, while the WREN-CR-VANET approach works well for moderately sized networks, it may become computationally expensive in dense and dynamic vehicular networks. As more vehicles join the network, cluster formation and route maintenance may affect the algorithm's performance and scalability. Furthermore, the present framework focuses primarily on routing and energy-saving issues. The problem of security threats, such as misbehaving nodes, route attacks, data injection, or privacy issues, is not considered in this research.

At the moment, the random waypoint mobility model is used because of its simplicity and widespread use in the VANET literature. The random waypoint mobility model cannot accurately reflect real-world traffic characteristics, such as lanes, traffic light controls, intersections, and other factors. As short-term future work, the framework will be tested in the SUMO traffic simulator using the SUMO-Veins/OMNeT++ integration under constrained road mobility to validate the present results.

In the future, research will be conducted to verify the effectiveness of the proposed framework using realistic vehicle network simulators and experimental test beds, thereby assessing its practicality. Possible additions to the framework include machine learning and deep reinforcement learning, security-aware routing algorithms, heterogeneous vehicular networks, and optimisation for V2X, 5G, and 6G communication technologies.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

S.S.R.I.: Methodology, Conceptualisation, Data curation, Validation, Writing—original draft, Writing—review & editing. A.M.: Project administration, Resources, Investigation, Writing—original draft, Writing—review & editing. I.D.: Software, Formal analysis, Methodology, Data curation, Writing—original draft, Writing—review & editing. Y.A.V.L.P.: Software, Formal analysis, Methodology, Data curation, Writing—original draft, Writing—review & editing. S.K.: Formal analysis, Software, Resources, Validation, Writing. P.S.: Formal analysis, Software, Resources, Validation, Writing. All authors had approved the final version.

References

[1] H. Hartenstein and K. Laberteaux, "A tutorial survey on vehicular ad hoc networks," *IEEE Commun. Mag.*, vol. 46, no. 6, pp. 164–171, Jun. 2008. doi: 10.1109/MCOM.2008.4539481

[2] G. Karagiannis *et al*., "Vehicular networking: A survey and tutorial," *IEEE Commun. Surveys Tuts.*, vol. 13, no. 4, pp. 584–616, 2011. doi: 10.1109/SURV.2011.061411.00019

[3] M. Y. Arafat and S. Moh, "A survey on cluster-based routing protocols for unmanned aerial vehicle networks," *IEEE Access*, vol. 7, pp. 498–516, 2019. doi: 10.1109/ACCESS.2018.2885539

[4] Y. W. Lin, Y. S. Chen, and S. L. Lee, "Routing protocols in vehicular ad hoc networks: A survey and future perspectives," *J. Inf. Sci. Eng.*, vol. 26, no. 3, pp. 913–932, 2010.

[5] C. Shao, S. Leng, Y. Zhang, A. Vinel, and M. Jonsson, "Analysis of connectivity probability in platoon-based vehicular ad hoc networks," in *Proc. Int. Wireless Commun. Mobile Comput. Conf. (IWCMC)*, 2014, pp. 706–711. doi: 10.1109/IWCMC.2014.6906443

[6] A. Naeem *et al.*, "Enhanced clustering-based routing protocol in vehicular ad-hoc networks," *IET Electr. Syst. Transp*., vol. 13, e12069, 2023. doi: 10.1049/els2.12069

[7] X. Xie, Y. D. Navaei, and S. Einy, "A clustering-based routing protocol using path pattern discovery method to minimise delay in VANET," *Wireless Commun. Mobile Comput.*, vol. 2023, 3776815, 2023. doi: 10.1155/2023/3776815

[8] S. Mirjalili, *Evolutionary Algorithms and Neural Networks: Theory and Applications*, Switzerland: Springer, 2019. doi: 10.1007/978-3-030-12127-3

[9] X. S. Yang, *Nature-Inspired Optimisation Algorithms*, Oxford, UK: Elsevier, 2014.

[10] I. Fister Jr., X. S. Yang, I. Fister, J. Brest, and D. Fister, "A brief review of nature-inspired algorithms for optimisation," arXiv Preprint, arXiv:1307.4186, 2013.

[11] A. Jalooli and A. Marefat, "Cluster stability-driven optimisation for

enhanced routing in heterogeneous vehicular networks," *Veh. Commun.*, vol. 47, 100745, 2024. doi: 10.1016/j.vehcom.2024.100745
[12] M. Badole, A. Thakare, and D. Oliva, "An improved multi-objective optimisation framework with a hybrid model for vehicular ad hoc network routing services," *Wireless Pers. Commun*., vol. 138, pp. 1–28, 2024. doi: 10.1007/s11277-024-11245-6
[13] G. D. Singh, M. Prateek, S. Kumar, M. Verma, D. Singh, and H. N. Lee, "Hybrid genetic firefly algorithm-based routing protocol for VANETs," *IEEE Access*, vol. 10, pp. 9142–9151, 2022. doi: 10.1109/ACCESS.2022.3142811
[14] S. Sahu and B. Tripathy, "Robust routing optimisation in VANET communication based on Bellman–Ford multitier metaheuristic algorithms," *Int. J. Commun. Syst*., vol. 38, pe6056, 2025. doi: 10.1002/dac.6056
[15] H. N. Abdulrazzak, G. C. Hock, N. A. M. Radzi, and N. M. L. Tan, "A new unsupervised validation index model suitable for energy-efficient clustering techniques in VANET," *IEEE Access*, vol. 11, pp. 67540–67555, 2023. doi: 10.1109/ACCESS.2023.3281302
[16] C. Z. Sirmollo and M. A. Bitew, "Mobility-aware routing algorithm for mobile ad hoc networks," *Wireless Commun. Mobile Comput.*, vol. 2021, 6672297, 2021. doi: 10.1155/2021/6672297
[17] R. Qun and S. M. Arefzadeh, "A new energy-aware method for load balance managing in the fog-based vehicular ad hoc networks (VANET) using a hybrid optimization algorithm," *IET Commun*., vol. 15, no. 13, pp. 1665–1676, 2021. doi: 10.1049/cmu2.12179
[18] S. A. Rashid, M. M. Hamdi, A. J. AbdulElah, Y. J. A. Rajab, and K. A. Zaaile, "Link stability based multipath routing and effective mobility prediction in cognitive radio enabled vehicular ad hoc network," *Bull. Electr. Eng. Inform.*, vol. 13, no. 1, pp. 215–221, Feb. 2024. doi: 10.11591/eei.v13i1.5222
[19] H. Jia, X. Zhou, J. Zhang *et al.*, "Superb fairy-wren optimization algorithm: A novel metaheuristic algorithm for solving feature selection problems," *Cluster Comput*., vol. 28, 246, 2025. doi: 10.1007/s10586-024-04901-w
[20] G. H. Alsuhli, Y. A. Fahmy, and A. Khattab, "Bio-inspired metaheuristic framework for clustering optimisation in VANETs," *IET Intell. Transp. Syst*., vol. 14, no. 9, pp. 1190–1199, 2020. doi: 10.1049/iet-its.2019.0366
[21] A. Kaur and Y. Kumar, "A multi-objective vibrating particle system algorithm for data clustering," *Pattern Anal. Applic*., vol. 25, pp. 209–239, 2022. doi: 10.1007/s10044-021-01052-1
[22] A. Sajithabegam and T. Menakadevi, "An enhanced energy and distance based optimized clustering and dynamic adaptive cluster-based routing in software defined vehicular network," *Telecommunication Systems*, vol. 87, no. 4, pp. 917–937, 2024. doi: 10.1007/s11235-024-01194-7
[23] M. Alazab, A. Al-Dubi, and M. A. Hasan, "Multi-objective cluster head selection using fitness averaged rider optimization algorithm for IoT networks in smart cities," *Int. J. Commun. Syst*., vol. 35, no. 12, e5201, 2022. doi: 10.1002/dac.5201
[24] R. S. Abujassar and E. Alharbi, "An intelligent and reliable routing framework for autonomous VANETs leveraging IoT integration," *Wireless Networks*, vol. 32, pp. 1177–1195, 2026. doi: 10.1007/s11276-026-04103-9
[25] S. W. Lee, K. S. Heo, M. A. Kim, D. K. Kim, and H. Choi, "Multiple-junction-based traffic-aware routing protocol using ACO algorithm in urban vehicular networks," *Sensors*, vol. 24, no. 9, 2913, 2024. doi: 10.3390/s24092913
[26] X. Chen, H. Tianfield, and W. Du, "Bee-foraging learning particle swarm optimization," *Appl. Soft Comput*., vol. 102, 107134, Apr. 2021. doi: 10.1016/j.asoc.2021.107134
[27] X. Li, W. Jiang, W. Wang, T. Zhou, K. Wang, and S. Liu, "Joint channel connectivity and interference management in DT-assisted cognitive vehicular networks," *Ad Hoc Networks*, vol. 165, 104094, 2026. doi: 10.1016/j.adhoc.2025.104094

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