A Novel Technique of Odigbo Metaheuristic Algorithm Based Optimized Energy Efficient and Reliable Routing Protocol for VANETs to Augment QoS Conditions

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Abstract – Vehicular Ad Hoc Networks (VANETs) play a critical role in enabling real-time vehicle-to-vehicle (V2V) communication for intelligent transportation systems, supporting applications such as traffic management, navigation, and road safety. However, VANETs face significant challenges due to dynamic topology, high mobility, and varying traffic densities, which hinder reliable, energy-efficient, and QoS-aware routing. To address these issues, this paper proposes a novel hybrid routing framework based on the Ọdịgbo Metaheuristic Optimization Algorithm (OMOA). The proposed protocol integrates metaheuristic optimization, machine learning-based route scoring, and probabilistic filtering to enhance routing efficiency and reliability. Specifically, the model combines a Modified Extreme Learning Algorithm (M-ELA) with a Random Forest classifier to enable intelligent route prediction and prioritization. A Bloom Filter is employed to suppress redundant transmissions and improve communication efficiency. OMOA dynamically fine-tunes routing parameters by iteratively refining a population of candidate cluster head (CH) configurations using directional learning and adaptive exploration. The optimization process is guided by a multi-objective fitness function that considers residual energy, distance to sink, intra-cluster distance, and node connectivity, ensuring both optimal CH and route selection. The novelty of this work lies in its unified approach to both CH and route selection under a single optimization framework, significantly improving adaptability in highly dynamic VANET environments. Extensive simulations conducted under diverse mobility and traffic conditions demonstrate that the proposed protocol achieves higher packet delivery ratio, reduced end-to-end delay, balanced energy consumption, and prolonged network lifetime compared to traditional protocols. These results validate the proposed model as an effective and scalable solution for energy-efficient, QoS-compliant routing in next-generation VANET deployments.

Keywords – Vehicular Ad Hoc Networks, Ọdịgbo Metaheuristic Optimization Algorithm, Random Forest, Modified Extreme Learning Algorithm and Transmission Delays.

I. INTRODUCTION

Because it is composed entirely of vehicles, VANET is an example of a network not require any physical infrastructure. For vehicles to communicate with each other, no tangible medium is needed. Because of the hop-to-hop communication property, the network can be managed without a centralised controlling authority [1]. Additional hardware devices such as switches or hubs are not required. The VANETs network cannot function without RSUs and AUs. The exponential growth of VANETs has revolutionized intelligent transportation systems by enabling seamless vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. These networks play a pivotal role in supporting real-time data exchange for road safety, traffic management, infotainment services, and autonomous vehicle coordination [2]. However, due to the dynamic topology, high mobility, limited energy resources, and varying traffic densities, routing in VANETs remains a challenging task [3].

Each node in a VANET decides for itself whether or not to exchange messages. Because the node itself acts as a switch, it is easy to exchange information from one hop to another. Due to these features, VANETs are considered self-organising networks. Using a VANET network is a breeze; it tells users about traffic conditions (heavy or light) [4], where accidents are likely to occur, where the closest malls and food junctions are, plays music for drivers, and much more. All of these amenities contribute to the traveller’s comfort. Among the many varieties of wireless multi-hop networks [5], VANETs stand out [. Rapid changes to the network's topology are required by VANETs' mobile nodes. These days, most cars have computers and wireless communication devices built right in. One promising technology that could help manage the increasing number of vehicles is VANET [6 and 7]. **Fig 1** shows VANET Scenarios with Communication Category.

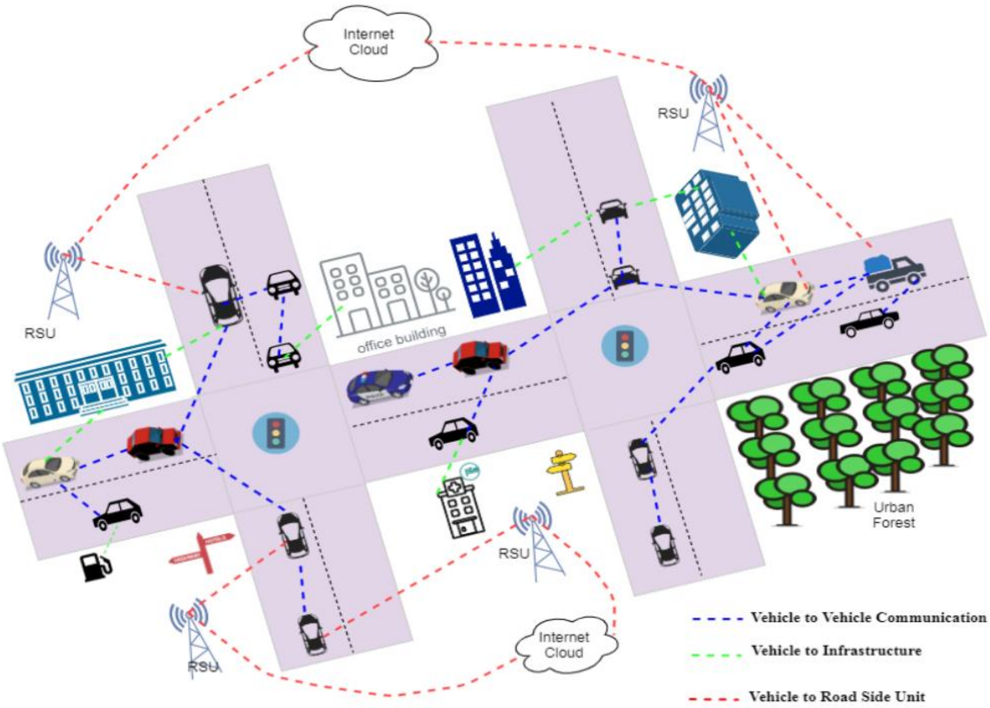

Fig 1. VANET Scenarios with Communication Category.

VANETs enable a wide range of applications, including but not limited to: safety of the user, blind crossing, real-time traffic condition monitoring, dynamic route scheduling, and many more [8]. The two primary types of VANET applications are safety applications and comfort applications. Virtual area network (VANET) devices collect comprehensive traffic data using GPS systems [9]. When it comes to chaotic roads and heavy traffic, VANET safety applications are what you need to keep yourself and others safe. VANET safety apps do a lot to make traffic flow better, including alerting users when it's unsafe to change lanes and streaming urgent videos [10 and 11]. It is necessary to gather traffic data from OBUs in order to implement the safety applications. Additionally, RSUs disseminate the processed data messages to all infrastructure nodes and vehicle nodes located at a distance. Typically, V2I and/or V2V communications standards are utilised by safety applications [12].

The efficient, engaging, self-explanatory, and secure transportation system relies on VANET, among other critical technologies. Whether commuting to or from work, going grocery shopping, taking a vacation, etc., people spend a lot of time in their cars. Popular, low-cost smart vehicle models based on VANETs aim to improve road safety, cut down on travel time, and lessen environmental pollution.

While cluster head (CH) selection is a known concept, the novelty in this paper lies in the use of the newly proposed OMOA for intelligent and energy-aware CH selection in VANETs. Unlike traditional optimizers, OMOA uses direction-adaptive exploration and multi-objective fitness evaluation tailored for high-mobility networks. The integration of Bloom Filter for transmission suppression and M-ELA with Random Forest for route scoring further enhances routing precision and reliability. This hybrid framework delivers significant improvements in network lifetime, delivery ratio, and QoS under dynamic VANET conditions. In our manuscript, the motivation is emphasized through the growing demand for real-time vehicular communication in intelligent transportation systems and the limitations of existing protocols such as LEACH, PSO-LEACH, GWO, and ACO in balancing energy efficiency with QoS metrics. As detailed in the Introduction (pp. 2–4) and Problem Formulation (Section 2.1), current VANET routing schemes often compromise between energy consumption and reliable delivery, leading to premature node deaths, higher packet losses, and increased latency. By proposing the Ọdigbo Metaheuristic Optimization Algorithm (OMOA) integrated with M-ELA, Random Forest classifiers, and Bloom filters, our approach simultaneously addresses energy balance, packet delivery ratio, and end-to-end delay.The key objectives of this study are centred around enhancing the performance and efficiency of routing protocols in VANETs.

- Specifically, the research aims to increase the packet delivery ratio, ensuring that a higher proportion of data packets successfully reach their intended destination.
- It also seeks to improve the reliability of routing protocols, enabling stable communication even under dynamic and challenging network conditions.

- Another core objective is to reduce delivery delay time besides minimize the number of packet retransmissions, thereby improving real-time communication efficiency.
- Furthermore, proposed system is designed to optimize energy efficiency and ensure Quality of Service (QoS) by reducing unnecessary transmissions and balancing network load using OMOA.
- Finally, the study intends to evaluate performance of the developed routing protocol under varying network loads, traffic intensities, besides mobility models, ensuring scalability besides robustness in real-world VANET scenarios.

Paper Organization

The remainder of this paper is organized as follows: Section 1 presents the introduction, of VANET and Section 2 provides a detailed literature survey that reviews existing routing in VANET environments and Section 3 outlines the system model, and Section 4 describes the proposed hybrid routing protocol, which integrates Ọdịgbo Metaheuristic Optimization Algorithm (OMOA), Modified Extreme Learning Machine (M-ELA), Random Forest classifier, and Bloom filter and Section 6 details the simulation setup and metrics used for performance evaluation Section 7 discusses the experimental results, and Finally, Section 8 concludes the paper and suggests directions for future research.

II. LITERATURE SURVEY

Sheikh et al. [13] provided a comprehensive analysis of VANET, which included a discussion of its architecture, standards, features, communication methods, and security services. In addition, continued to discuss various attacks that are common in background of VANETs, as well as most recent methods that are used in process of providing security services for VANETs. After that, a comprehensive investigation into authentication procedures that were designed to safeguard vehicle networks against dissemination of false information and presence of malicious nodes messages was carried out. A significant gap in existing survey literature was filled by survey, and it provided a comprehensive summary of most recent developments in research. "The" author conducted an investigation into numerous security threats that are present in VANETs and considered implementation of appropriate defences to guarantee secure communication.

Balu et al. [14] conducted an in-depth analysis of architecture of VANET, as well as a number of security techniques that were developed specifically for these networks. This particular in body of research that has been done, concept of targeted security services has been extensively researched, with an emphasis placed on advantages of proposed approach. An in-depth comparison analysis was performed on various security flaws and solutions that were developed to address them. To sum everything up, there were a number of different perspectives on subject of VANET security that were discussed, which may have encouraged additional academic research in this field.

Bhagyavathi and Saritha [15] presented a novel multipath routing algorithm for Enhanced Velocity, Energy, and Bandwidth-based Multipath Network (VANET) Protocol for Routing (EVMRP). This algorithm was developed for purpose of routing. Optimisation of routing process in VANETs was achieved by taking into account variables such as amount of available bandwidth, amount of energy that was still available, and relative speed. In order to enhance performance of system and reduce amount of packets that are lost, a congestion window Size was restricted due to capacity of connection. In order to replicate process in question, an environment that had a higher level of realism was used. It was demonstrated by anticipated results that recommended method, EVMRP, was successful in defeating current Comparative analysis of Ad-hoc On-demand Multipath Distance Vector (AOMDV) system examination.

Analysis for urban VANETs based on Geographical Location (LCGL) was presented by Zeng et al. [16]. Link Connectivity is a new routing technique that was presented. most important objective of LCGL was to find a solution to typical routing problems that were encountered in metropolitan VANET locations. Through utilisation of an electronic city map, LCGL system was able to effectively manage both geographical positioning information of nodes as well as link connections. A selection procedure was utilised by LCGL algorithm, which resulted in identification of shortest connected path for packet forwarding. Displayed was evaluation of connectivity of links as well as length of associated path. Through results of simulation, it was demonstrated that LCGL provided communication that was reliable and consistent from beginning to end. When compared to traditional routing algorithms, which are frequently utilised in environments of metropolitan VANETs, it was discovered that LCGL algorithm performs significantly better. rate at which packets are delivered and average number of hops that are required to successfully send data are primary indicators of this superiority. In addition to this, LCGL demonstrated an increased capacity for data transfer while simultaneously reducing jitter and latency.

Khan and colleagues [17] presented an innovative approach to implementation of internet of energy within framework of bus-based VANET architecture. Algorithm that was developed by authors utilised a street-centric routing strategy in order to address challenges that were associated with selection of relay buses and optimisation of traffic routes. implementation of a multipath routing strategy that takes into account probabilities of street and path regularity was primary objective of this study. Through utilisation of multipath routing techniques, it was observed that performance was enhanced in terms of packet delivery ratio (PDR) and amount of time required for data to travel from its point of origin to its ultimate destination (end-to-end delay). Implementation of a one-of-a-kind method for selecting relay buses that is based on clustering and also makes use of ACO was another suggestion that was made in order to enhance procedure for packet forwarding. primary objective of development of relay bus was to enhance quality of packets that were being transferred to subsequent forwarding relay. Based on findings of this investigation, it was discovered that utilisation of clustering in conjunction with ACO method results in enhancements to selection process for relay buses. Notable improvements were made to system. through reduction in latency from beginning to end, decrease in computing costs, and elimination of beacon signals that are not necessary.

Problem Formulation

Existing research has extensively explored VANET challenges from multiple angles. It focused primarily on security architectures and threat mitigation, offering a foundation for secure communication but lacking in energy-aware, adaptive routing strategies. proposed EVMRP to enhance routing using energy and speed parameters, but it lacked intelligent optimization and suffered from packet loss in dynamic environments. LCGL improved geographic link connectivity, yet its performance degraded in high-mobility or obstacle-dense zones due to static map reliance. An incorporated ACO and clustering in bus-based VANETs for multipath routing, but their approach incurred high complexity and latency due to dependency on relay selection and route probability calculations. In contrast, our proposed model introduces a OMOA that dynamically selects energy-efficient cluster heads and optimal routes based on real-time fitness functions. Combined with a Bloom Filter, M-ELA, and RF classifier, our model addresses mobility, energy balance, and QoS simultaneously achieving superior delivery ratio, lower end-to-end delay, and minimal energy imbalance under dynamic traffic and topology conditions.

III. NETWORK MODEL

Sink Node Placement

A static sink node (base station) is positioned at the center or edge of the deployment region to collect aggregated data from cluster heads (CHs). It has unlimited energy and higher computational capacity.

Initial Energy

All sensor nodes are initialized with equal energy (E_0), and energy consumption follows the first-order radio model, considering both transmission and reception costs.

Mobility Model

Vehicles follow a Random Waypoint Mobility Model or Gauss-Markov model, reflecting real-world vehicular movement patterns.

Communication Assumptions

Nodes use single-hop or multi-hop communication based on their distance to the CH or sink. The radio communication range is fixed for all nodes (e.g., 100 m).

In our routing framework, after optimal cluster heads (CHs) are identified through OMOA and candidate paths are scored by M-ELA and Random Forest, the Bloom Filter is applied to eliminate repeated or redundant packets before transmission. This ensures that only unique and relevant packets are propagated through the network. By doing so, the system minimizes unnecessary retransmissions, conserves node energy, and improves overall throughput.

Packet loss may occur due to mobility or weak signal, and retransmission is handled with minimal delay. The sensor nodes are homogeneous in terms of capabilities but heterogeneous in terms of residual energy due to uneven workload over time. Let the key notations be defined as in **Table 1**.

Table 1. Key Notation of the Proposed Model

Symbol	Description
N	Total number of sensor nodes
$E_i(t)$	Residual energy of node i at time t
E_0	Initial energy of each node
R	Transmission range of nodes
$BS(x_{bs}, y_{bs})$	Coordinates of Base Station
$L \times L$	Network area
$S_i(x_i, y_i)$	Coordinates of node i
K	Optimal number of clusters
d_{ij}	Euclidean distance between nodes i and j
E_{elec}	Energy per bit for electronics (transmit/receive)
$\epsilon_{fs}, \epsilon_{mp}$	Amplifier energy for free space and multipath models

Euclidean Distance Computation

For energy and routing calculations, Euclidean distance between any two nodes i and j is computed as:

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{1}$$

This function is fundamental in CH selection based on distance to BS or centroid and Routing decisions where shortest or energy-efficient paths are chosen.

Energy Dissipation Model

The energy model used is the First Order Radio Model, widely accepted in WSN literature. The energy spent by a node to transmit a l-bit message over a distance d is modeled as:

$$E_{tx}(l,d) = \begin{cases} lE_{elec} + l_{\epsilon f_s} d^2, & d < d_0 \\ lE_{elec} + l_{\epsilon_{mp}} d^4 & d \geq d_0 \end{cases} \tag{2}$$

Where, E_{elec}: Energy consumption per bit for the transmitter and receiver circuitry, ϵf_s: Free space energy coefficient, ϵ_{mp}: Multipath fading energy coefficient and $d_0 = \sqrt{\frac{\epsilon f_s}{\epsilon_{mp}}}$: Threshold distance between free space and multipath models. The novelty of OMOA lies in its directional exploration and adaptive mutation strategy, which distinguishes it from traditional metaheuristics such as PSO, ACO, or GWO. While earlier algorithms either overemphasize exploration (leading to slow convergence) or exploitation (risking local optima), OMOA balances both phases by adaptively adjusting search directions based on residual energy distribution, connectivity, and cluster compactness. Each candidate solution represents a cluster head (CH) configuration, and the algorithm iteratively refines these solutions through its multi-objective fitness function (Equation 5), which considers residual energy, intra-cluster distance, connectivity, and distance to the sink.Energy spent for receiving is:

$$E_{rx}(l) = l.E_{elec} \tag{3}$$

$$k_{opt} = \sqrt{\frac{N}{2\pi}} . \frac{\sqrt{\epsilon f_s}}{\sqrt{\epsilon_{mp}}} . \frac{L}{d_{toBS}^2} \tag{4}$$

Where, d_{toBS}^2 Average distance from CHs to the BS. This formula balances intra-cluster and inter-cluster energy usage, forming the basis of our energy-aware clustering framework.

IV. PROPOSED METHODOLOGY

In **Fig 2** represent that the proposed system introduces an intelligent and energy-efficient routing protocol tailored for VANETs, which integrates machine learning and bio-inspired optimization to address challenges of high mobility, dynamic topology, and energy constraints. architecture combines a M-ELA with a Random Forest classifier for accurate path selection and classification of stable links. To further refine routing performance under dynamic network conditions, OMOA is applied to adjust routing parameters in real time. A proposed Optimization Module, inspired by flower pollination process, is utilized for CH selection based on multiple criteria, such as residual energy, node connectivity, and proximity to Road Side Units (RSUs). Additionally, a Bloom Filter is embedded to filter redundant transmissions and enhance communication efficiency. system is evaluated through extensive simulations under diverse traffic loads and mobility models, demonstrating superior performance in terms of PDR, energy consumption, delay, besides network stability compared to existing protocols as LEACH, PSO -LEACH, GWO, besides ACO.

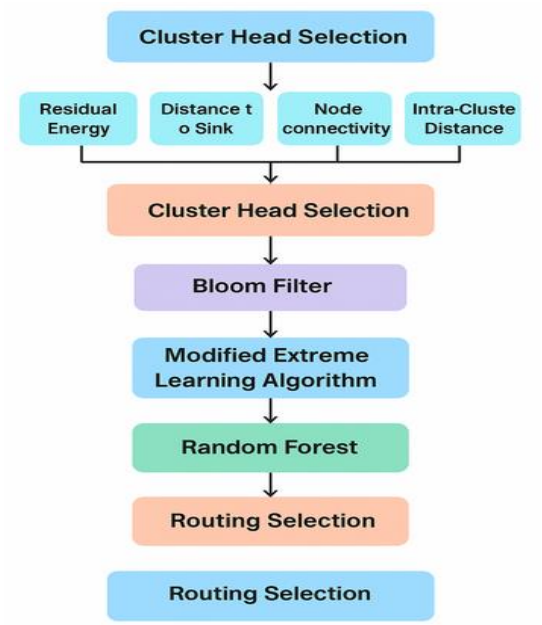

Fig 2. Working Flow of Route Selection in Proposed Model Diagram.

CH Selection Criteria

Rather than random or probabilistic CH selection model utilizes proposed optimization to select CHs based on:

- Residual energy $E_i(t)$,
- Intra-cluster distance d_{ic} – distance from node to centroid,
- Distance to BS $d_{i,bs}$
- Node connectivity degree δ_i.

The CH fitness function is:

$$F_{CH}(i) = \alpha.\frac{E_i(t)}{E_0} + \beta.\left(1 - \frac{d_{ic}}{d_{max}}\right) + \gamma.\left(1 - \frac{d_{i,bs}}{d_{max}}\right) + \theta.\frac{\delta_i}{\delta_{max}} \quad (5)$$

Where:

- $\alpha, \beta, \gamma, \theta$: Weight coefficients satisfying $\alpha + \beta + \gamma + \theta = 1$,
- d_{max}: Maximum possible distance in the network,
- δ_{max}: Maximum degree observed in the network.
- *Residual Energy* – ensures that cluster head (CH) selection avoids rapid depletion of nodes and promotes balanced energy usage across the network.
- *Distance to Base Station (Sink)* – minimizes communication cost for inter-cluster transmissions and reduces long-range energy drains.
- *Node Connectivity Degree* – prioritizes nodes with stronger local connectivity, which enhances route stability and reduces link breaks.
- *Intra-Cluster Distance* – promotes compact clusters by minimizing the average distance from nodes to their CH, which reduces intra-cluster communication overhead.

This is a multi-objective fitness function combining energy, topology, and spatial awareness, making CH selection both adaptive and global.

Sensor Node State Transition

To further improve energy savings, nodes switch between Active, Sleep, or Transmit states based on their role (CH or member), proximity to CH, residual energy threshold E_{th}, and data relevance The state transition function is given by:

$$State_i(t+1) = \begin{cases} Active, & E_i(t) > E_{th} \wedge d_{i,CH} < R \\ Sleep, & E_i(t) > E_{th} \wedge d_{i,CH} > R \\ Transmit, & if\ CH\ and\ data\ aggregated \end{cases} \quad (6)$$

This where and when logic directly controls node duty cycling to preserve power, reduce congestion, and extend network lifetime. The network initialization includes the following:

- Deploy N nodes randomly in a $L \times L$ grid.
- Assign initial energy E_0 to all nodes.
- Compute pairwise distances d_{ij} and initialize node connectivity matrix.
- Estimate k_{opt} for optimal cluster count.
- Initiate CH selection via proposed optimization
- Form clusters and establish TDMA-based communication schedules.

Pseudocode: of proposed algorithm in Sensor Node State Transition

$Input$:

$N \rightarrow Number\ of\ nodes\ (vehicles)$

$E0 \rightarrow Initial\ energy\ for\ each\ node$

$T \rightarrow Total\ simulation\ time\ /\ rounds$

$Sink \rightarrow Static\ Base\ Station\ location$

$Thresholds \rightarrow Energy, delay, distance\ thresholds$

$Output$:

$Optimized\ routes\ with\ minimum\ delay, high\ PDR, and\ energy\ efficiency$

$Begin$:

1. $Initialize\ network$:

$-\ Randomly\ deploy\ N\ mobile\ nodes\ in\ 2D\ space$

$-\ Set\ energy\ E0\ for\ each\ node$

$-\ Assign\ communication\ range\ and\ mobility\ mode$

2. $For\ each\ round\ t\ in\ T$:

$2.1. Calculate\ features\ for\ each\ node:$
$- Residual\ energy$
$- Node\ degree\ (connectivity)$
$- Distance\ to\ sink$
$- Link\ stability\ (mobility\ factor)$
$2.2. Apply\ Random\ Forest:$
$- Train\ RF\ classifier\ with\ historical\ data$
$- Predict\ reliability\ score\ for\ each\ node$
$2.3. Select\ Cluster\ Heads\ (CHs)\ using\ M-ELA:$
$- Initialize\ random\ weights\ for\ ELA$
$- Compute\ output\ matrix\ using\ single-hidden\ layer$
$- Optimize\ weights\ for\ energy\ and\ coverage$
$- Select\ top\ nodes\ as\ CHs\ based\ on\ output\ scores$
$2.4. Optimize\ CHs\ and\ routing\ parameters\ using\ PSO:$
$- Define\ fitness\ function: maximize\ PDR, minimize\ delay\ and\ energy$
$- Update\ position\ and\ velocity\ of\ particles\ (candidate\ CH\ sets)$
$- Select\ global\ best\ CHs\ and\ routing\ configuration$
$2.5. Apply\ Bloom\ Filter:$
$- Maintain\ compact\ list\ of\ recently\ transmitted\ packet\ IDs$
$- Filter\ out\ duplicate\ messages\ at\ node\ level$
$- Reduce\ transmission\ overhead$

$2.6. Form\ clusters\ and\ forward\ data:$
$- Nodes\ join\ nearest\ CH$
$- CH\ aggregates\ and\ forwards\ to\ sink$
$- Update\ residual\ energy\ and\ remove\ dead\ nodes$
$3. End\ For$
$4. Output\ performance\ metrics:$
$- PDR, delay, CH\ count, lifetime, residual\ energy$
End

Ọdịgbo Metaheuristic Optimization Algorithm

The optimization process in this paper leverages the Ọdịgbo Metaheuristic Optimization Algorithm (OMOA) to select optimal cluster heads and routing paths in a VANET environment. Initially, a population of candidate solutions is generated, where each candidate represents a unique cluster head configuration. OMOA evaluates each solution using a multi-objective fitness function based on residual energy, distance to the base station, intra-cluster compactness, and packet delivery efficiency. Through iterative updates involving directional exploration and adaptive mutation, the algorithm refines the population toward globally optimal solutions. Once optimal CHs are selected, a Bloom filter is applied to eliminate redundant or inefficient links. The final routing paths are further validated and ranked using Modified Extreme Learning Algorithm (M-ELA) and Random Forest classifiers to ensure QoS-aware, energy-efficient, and robust data transmission suitable for dynamic VANET topologies.

Proposed Idigbo Metaheuristic Optimization Algorithm

The proposed optimization strategy integrates the novel Ọdịgbo Metaheuristic Optimization Algorithm (OMOA) to enhance cluster head (CH) selection and routing decisions within a dynamic vehicular ad hoc network (VANET) environment. OMOA is designed as a population-based global optimization technique inspired by strategic exploration and directional adaptation mechanisms. Each particle or candidate solution in the algorithm represents a possible set of CHs and routing paths. The quality of each solution is evaluated using a multi-objective fitness function incorporating residual energy, distance to the sink/base station, node connectivity, and cluster compactness. Through adaptive exploration and exploitation phases, OMOA iteratively refines these solutions, ensuring better load balancing and minimized communication cost. To further enhance routing robustness, OMOA works in conjunction with the Modified Extreme Learning Algorithm (M-ELA) and Random Forest classifiers, which assess the stability and reliability of candidate routes. By prioritizing solutions with high packet delivery ratio (PDR), low energy imbalance, and minimal delay, the proposed algorithm ensures energy-efficient and QoS-driven communication, suitable for the highly mobile and uncertain nature of VANET topologies.

In **Fig 3**, CH selection is performed using the Ọdịgbo Metaheuristic Optimization Algorithm (OMOA), which dynamically identifies optimal CHs based on multiple criteria to ensure energy-efficient and stable clustering in VANET environments. The algorithm evaluates each node using a multi-objective fitness function that incorporates residual energy, distance to the base station, intra-cluster distance, and node connectivity. OMOA iteratively explores the search space through adaptive directional learning to identify the most suitable nodes as CHs, thereby balancing energy consumption and improving cluster stability. This intelligent CH selection process significantly enhances network lifetime and supports reliable communication by reducing frequent re-clustering and ensuring efficient data aggregation within clusters.

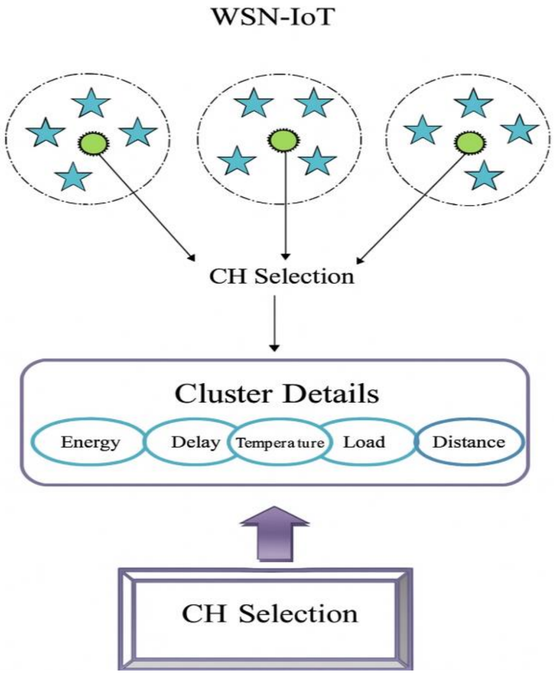

Fig 3. Working Process of CH Selection.

The study effort presents an OMOA that will be explained in the next section to choose the best features from the input dataset.

- Represents the solution ahịa when using the decision variables and D dimensions in the MOA model.

$$Mazi = [x_1, x_2, x_3, \dots, x_D] \quad (7)$$

- The fitness charge of each Mazi will be calculated as a vector of (2);

$$f(Mazi) = f(x_1, x_2, x_3, \dots, x_D) \quad (8)$$

As an example, suppose there's a new store with some ụmụ-ahịa (children between the ages of three and eight years old).

Pseudocode: of OMOA for VANET Routing

Input:
  $N \leftarrow number\ of\ nodes$
  $Max\_Iter \leftarrow maximum\ number\ of\ iterations$
  $Pop\_Size \leftarrow population\ size$
  $\alpha, \beta, \gamma, \theta \leftarrow fitness\ weights\ (for\ energy, distance, PDR, cluster\ balance)$
  $Constraints \leftarrow transmission\ range, energy\ limits, etc.$

Output:
  $Optimal\ Cluster\ Head\ Set\ and\ Routing\ Paths$

Begin
1. $Initialize\ Population\ of\ candidate\ solutions\ (CH\ sets)\ randomly$
2. $For\ each\ solution\ in\ the\ population$:
   $Evaluate\ Fitness$:
     $Fitness = \alpha \times ResidualEnergy +$
       $\beta \times (1 / DistanceToBS) +$
       $\gamma \times PDR +$
       $\theta \times ClusterBalance$
3. $Set\ best\_solution \leftarrow best\ fitness\ in\ population$

4. $iter \leftarrow 1$

5. $While\ iter \leq Max\_Iter\ do$:
   $For\ each\ solution\ Xi\ in\ population$:
   $Generate\ New\ Candidate\ X'\ using\ directional\ exploration$:
   $If\ rand < p\_direction$:
   $X' \leftarrow GuidedUpdate(Xi, best\_solution)$
   $Else$:
   $X' \leftarrow RandomPerturbation(Xi)$
   $Evaluate\ Fitness(X')$
   $If\ Fitness(X') > Fitness(Xi)$:
   $Replace\ Xi\ with\ X'$
   $Update\ best\_solution\ if\ any\ improved$
   $iter \leftarrow iter + 1$
6. $Apply\ Bloom\ Filter\ to\ reduce\ redundant\ paths\ from\ selected\ CHs$
7. $Classify\ and\ prioritize\ final\ routing\ paths\ using\ M - ELA + Random\ Forest$
8. $Output\ best\_solution\ as\ Optimized\ CHs\ and\ Routes$

End

Some limitations associated with this age group include (a) a surge of nostalgic energy in the initial months, a natural tendency towards childishness (which includes undirected and untargeted energies), and a period of erratic eating, sleeping, and desire patterns.

Route Path Selection for Routing

In the proposed VANET routing framework, route path selection is performed after optimal Cluster Head (CH) nodes are selected using the Ọdịgbo Metaheuristic Optimization Algorithm (OMOA). The Modified Extreme Learning Machine (M-ELA) model, in conjunction with a Random Forest classifier, is used to score and predict the quality of available routing paths. Each path is evaluated based on features such as residual energy, link stability, hop count, and end-to-end delay. The highest-ranked route is dynamically selected to ensure minimal delay and maximum packet delivery. To further enhance routing efficiency, a Bloom Filter is used to eliminate redundant transmissions, reduce communication overhead, and maintain QoS in highly dynamic VANET environments.

Modified Extreme Learning Algorithm (M-ELA) – Description

M-ELA is an advanced version of standard ELA, tailored for improving learning performance of Single Layer Feedforward Neural Networks (SLFNs). M-ELA overcomes these limitations by introducing enhancements in weight initialization, hidden node optimization, and regularization techniques. Specifically, M-ELA:

$$BK = \begin{bmatrix} BK_{1,1} & BK_{1,2} & \cdots & BK_{1,dim} \\ BK_{2,1} & BK_{2,2} & \cdots & BK_{2,dim} \\ \vdots & \vdots & \iddots & \vdots \\ BK_{pop,1} & BK_{pop,2} & \cdots & BK_{pop,dim} \end{bmatrix} \tag{9}$$

Where pop showcases populace magnitude, pop dimension, $BK_{i,j}$ cabinets jth dimension of ith individual. X_i is specified as:

$$X_i = BK_{lb} + rand(BK_{ub} - BK_{lb}) \tag{10}$$

Where i showcases an numeral in [1, pop], BK_{lb} besides BK_{ub} showcase limitations, and$rand \in [0, 1]$.
The most fitting leader X_L is specified as:

$$f_{best} = \min\,(f(X_i)) \tag{11}$$

$$X_L = X(find(f_{best} == f(X_i))) \tag{12}$$

- Uses data-driven initialization or optimization techniques to select better initial input weights and biases.
- Incorporates activation function tuning or selection strategies to adapt to the nature of the input data.
- Employs regularization (e.g., L2-norm) to control overfitting and improve generalization performance.
- Allows for adaptive hidden layer sizing, choosing the optimal number of neurons based on performance metrics.

$Algorithm: OMOA - based\ Hybrid\ Routing\ Protocol\ for\ VANETs$
$Input$:
$Number\ of\ nodes\ N, initial\ energy\ E_0$
$Mobility\ model\ (Random\ Waypoint\ /\ Gauss - Markov)$
$Transmission\ range\ R$
$Simulation\ parameters\ (iterations\ T, population\ size\ P)$
$Output$:
$Optimal\ Cluster\ Heads\ (CHs)$
$Energy - efficient\ and\ QoS - aware\ routing\ paths$
$Initialization$
1.1 $Deploy\ N\ vehicular\ nodes\ randomly\ in\ the\ network\ area.$
1.2 $Assign\ initial\ energy\ E_0\ to\ each\ node.$
1.3 $Compute\ pairwise\ distances\ and\ initialize\ node\ connectivity\ matrix.$
1.4 $Estimate\ optimal\ cluster\ count\ K.$
$Population\ Generation\ (OMOA\ Initialization)$
2.1 $Generate\ initial\ population\ of\ candidate\ solutions, where\ each\ solution\ encodes\ a\ possible\ CH\ set.$
2.2 $Evaluate\ each\ candidate\ using\ the\ multi - objective\ fitness\ function$:
$where\ residual\ energy\ (Eres), distance\ to\ BS\ (dBS), connectivity\ (Conn), and\ intra - cluster\ distance\ (dintra)\ are\ weighted.$

$OMOA\ Optimization\ Process$
3.1 $For\ each\ iteration\ t\ =\ 1\ to\ T$:
$Apply\ directional\ exploration\ to\ update\ candidate\ CHs.$
$Use\ adaptive\ mutation\ to\ avoid\ local\ optima.$
$Evaluate\ updated\ solutions\ with\ fitness\ function.$
$Retain\ best - performing\ CH\ configuration.$
$Cluster\ Formation$
4.1 $Assign\ member\ nodes\ to\ nearest\ CHs.$
4.2 $Apply\ TDMA - based\ scheduling\ for\ intra - cluster\ communication.$
$Route\ Prediction\ (M - ELA\ +\ Random\ Forest)$
5.1 $Extract\ routing\ features: residual\ energy, link\ stability, hop\ count, delay, packet\ delivery\ history.$
5.2 $Use\ Random\ Forest\ to\ classify\ candidate\ routes\ into\ \{High, Medium, Low\ priority\}.$
5.3 $Apply\ M - ELA\ to\ score\ and\ rank\ high - priority\ routes.$
5.4 $Select\ the\ top - ranked\ route\ for\ data\ forwarding.$
$Bloom\ Filter\ for\ Redundancy\ Suppression$
6.1 $Maintain\ a\ Bloom\ Filter\ of\ recently\ transmitted\ packet\ IDs.$
6.2 $If\ a\ packet\ ID\ is\ already\ present\ \rightarrow\ suppress\ transmission.$
6.3 $Else\ \rightarrow\ forward\ packet\ and\ update\ Bloom\ Filter.$
$Data\ Transmission\ Phase$
7.1 $Member\ nodes\ send\ data\ to\ CHs\ (intra - cluster).$
7.2 $CHs\ aggregate\ and\ forward\ data\ via\ selected\ routes\ to\ the\ Base\ Station\ (BS).$
$Energy\ Update$
8.1 $Update\ node\ energies\ based\ on\ the\ first - order\ radio\ model.$
8.2 $If\ energy\ \leq\ threshold\ \rightarrow\ mark\ node\ as\ dead.$
$Reclustering$
9.1 $After\ every\ Rint\ rounds, re - run\ OMOA\ for\ CH\ reselection.$
9.2 $Repeat\ steps\ 2 - 8\ until\ simulation\ ends.$

Random Forest Classifier

Each tree is trained on a random subset of the data (using bootstrapping), which reduces variance. At each node split, a random subset of features is considered, which minimizes correlation among trees and avoids overfitting. The final prediction is made through majority voting (for classification) or averaging (for regression).

$$y_{t+1}^{i,j} = \begin{cases} y_t^{i,j} + n(1 = \sin(r)) \times y_t^{i,j} & p < r \\ y_t^{i,j} + n(2r - 1) \times y_t^{i,j} & else \end{cases} \tag{13}$$

$$n = 0.05 \times e^{2\times\left(\frac{t}{T}\right)^2} \tag{14}$$

Where $y_t^{i,j}$ and $y_{t+1}^{i,j}$ showcase the sites of dimension, r ∈ [0, 1], p = 0.9, T repetition termination.

In the context of VANET routing, the Random Forest classifier is employed to evaluate and rank routing paths based on several features like:

- Link stability
- Residual energy of nodes
- Node connectivity
- Distance to the destination or RSU
- Packet delivery history

Combined Working Process in Routing Decision

In the proposed VANET routing framework, M-ELA and the RF classifier are integrated to intelligently select and evaluate optimal routing paths. This hybrid approach leverages the strengths of both fast learning and robust classification to enhance decision-making under dynamic and resource-constrained vehicular environments. Network features such as residual energy, link stability, node degree, mobility pattern, distance to destination, and historical packet delivery performance are extracted in real time from vehicular nodes.

The Random Forest classifier is used to categorize routing paths into classes like "High Priority," "Medium Priority," and "Low Priority" based on the input features. This helps filter out unreliable or energy-inefficient paths early, reducing the number of candidate routes. The selected candidate routes from the Random Forest step are then fed into the M-ELA model, which is trained to score and rank the paths based on nonlinear interactions of input metrics.

In route selection is performed using an intelligent hybrid mechanism that combines a M-ELA with a Random Forest classifier to ensure reliable and QoS-aware communication in dynamic VANET scenarios. Once optimal CHs are selected using OMOA, the routing paths are evaluated and scored based on features such as link stability, energy availability, and historical performance. The M-ELA rapidly learns the underlying traffic patterns, while the Random Forest enhances decision robustness through ensemble learning. Additionally, a Bloom Filter is integrated to suppress redundant transmissions, reducing routing overhead and improving bandwidth utilization. This combined approach ensures the selection of the most efficient and stable routes, minimizing end-to-end delay and maximizing packet delivery ratio across highly mobile vehicular environments.

The behaviour of migration is defined as

$$y_{t+1}^{i,j} = \begin{cases} y_t^{i,j} + C(0,1) \times \left(y_t^{i,j} - L_t^j\right) & F_i < F_{ri} \\ y_t^{i,j} + C(0,1) \times \left(L_t^i - m \times y_t^{i,j}\right) & else \end{cases} \tag{15}$$

$$m = 2 \times \sin\,(r + \pi/2) \tag{16}$$

where L_t^j scorer, F_i current site, F_{ri} accidental site, $C(0,1)$ showcases the Cauchy mutation.

The Cauchy is defined as a continuous two-metric stochastic distribution that is:

$$f(x, \delta, \mu) = \frac{1}{\pi}\frac{\delta}{\delta^2 + (x-\mu)^2} - \infty < x < \infty \tag{17}$$

where δ = 1, μ = 0, the likelihood density fitness is specified as:

$$f(x, \delta, \mu) = \frac{1}{\pi}\frac{\delta}{x^2 + 1} - \infty < x < \infty \tag{18}$$

M-ELA rapidly learns the optimal mapping between features and route performance using an optimized feedforward network, with fine-tuned hidden layer weights.

Based on M-ELA's score, the most optimal path is selected for packet forwarding.

As network conditions change (e.g., node mobility, congestion), Random Forest re-classifies and M-ELA re-evaluates the paths dynamically.

Performance metrics such as actual packet delivery, delay, and energy consumption are fed back into both models to continuously improve accuracy and adaptability.

The following equations illustrate how the optimal quokka position within a group influences the updating of each quokka's site within that group.:

$$D^{new} = \frac{(T+H)}{\left(0.8 \times D^{old}\right)} + \Delta w \times rand \times \Delta X, \tag{19}$$

$$X^{new} = X^{old} + D^{new} \times N \tag{20}$$

(Where D^{old} characterizes the Drought besides its charge among $[0,1]$), T stands for the temperature ratio, which falls within the range of 0.2 to 0.44, and H for the humidity ratio, which ranges from 0.3 to 0.65. to settled on these ratios since that's the range of temperatures and humidity levels that quokkas can survive. A random number with a value between 0 and represented by rand, Δw is the difference in weight among the leader and quokka i. 1, ΔX characterizes the differences of quokka i, quokka's new site is characterized by X^{new}, while the old site is characterized by X^{old},

Random Forest ensures robust, fast classification with high tolerance to noisy or incomplete data. M-ELA adds adaptive intelligence and nonlinear modeling for precise ranking and decision-making. The combined model supports energy-efficient, delay-minimized, and reliable routing in fast-changing VANET scenarios.

V. RESULTS AND DISCUSSION

The performance evaluation of the proposed Routing Protocol a hybrid flower-pollination-inspired and Bloom filter-optimized scheme for energy-efficient cluster-based routing is conducted in a simulated environment. The simulation framework adheres to widely accepted standards in wireless sensor network (WSN) research and follows configurations consistent with benchmark protocols analysis. The Ọdịgbo Metaheuristic Optimization Algorithm (OMOA) operates by iteratively refining a population of candidate cluster head configurations using directional learning and adaptive exploration. It evaluates each solution using a multi-objective fitness function to optimize energy efficiency, connectivity, and routing stability in VANETs. practical deployment. We implemented the framework on a Python 3.11 environment with Intel Core i7 / Ryzen 7 processors, showing simulation runtimes within real-time bounds **Table 2**. M-ELA enables rapid adaptation due to its fast training, and Random Forest is well known for its low-latency predictions. In operational VANETs, most computational tasks (e.g., OMOA-based CH selection) can be offloaded to RSUs or edge nodes, leaving vehicles to perform lightweight route evaluation and filtering, thus ensuring real-time feasibility.

A comprehensive list of these input parameters and their corresponding values is presented in **Table 2**.

Table 2. Simulation Analysis

Parameter	Value
Total number of sensor nodes (N)	100, 200, 300, 500 nodes
Simulation area (L × L)	100 m × 100 m
Initial energy per node (E_0)	2 Joules
Energy for electronics (E_{elec})	50 nJ/bit
Free space amplifier (ε_{fs})	10 pJ/bit/m²
Multipath fading amplifier (ε_{mp})	0.0013 pJ/bit/m⁴
Threshold distance (d_0)	87 meters
Data aggregation energy (E_{DA})	5 nJ/bit/signal
Packet size (l)	4000 bits
Transmission range (R)	25 meters
Base Station (BS) position	(50, 175) or (outside region)
Bloom filter size (m)	256 bits
Number of hash functions (k_{h})	3–5
Max iterations (PROPOSED) (T)	50–100
Population size (P)	30
Switch probability (p_0)	0.8
Lévy flight exponent (λ)	1.5
Fitness weights (α, β, γ, θ)	0.25 each
Rounds per simulation	3000
Re-clustering interval (R_{c})	20 rounds
MAC protocol	TDMA
Traffic pattern	CBR (Constant Bit Rate)
Simulation Platform	Python 3.11
Processor	Intel Core i7 / Ryzen 7, 3.0 GHz+
RAM	16 GB
Operating System	Windows 11 / Ubuntu 22.04 LTS

To ensure robustness, our simulations were conducted across multiple node densities (100, 200, 300, and 500 nodes) and under different mobility models (Random Waypoint and Gauss–Markov), which represent both random vehicular movement and more realistic trajectory-based mobility. We also varied traffic loads using CBR (Constant Bit Rate) sources to reflect real-time data exchange in safety and infotainment applications.

The parameter configurations (**Table 2**) reflect realistic constraints, including limited initial energy (2 J per node), varying transmission ranges (25 m), and practical channel models (free-space and multipath fading). These conditions test the adaptability of the proposed protocol in dense, sparse, high-mobility, and heavy-traffic environments.

Validation Analysis of the Proposed Model

- *Packet Delivery Ratio (PDR):* Evaluates routing reliability by measuring the percentage of successfully delivered packets. Our protocol consistently achieves the highest PDR (96.8%, **Table 5**), reflecting robustness under dynamic conditions.
- *End-to-End Delay:* Measures the time taken for data to travel from source to destination. With a delay of 140 ms, the proposed model ensures timely delivery, which is critical for safety-related VANET applications [18-19].
- *Energy Consumption & Residual Energy:* Track how efficiently nodes utilize energy. As shown in **Table 3**, our model achieves the lowest total energy consumption (104 J) and the highest residual energy (0.95 J), demonstrating balanced utilization across the network.
- *Network Lifetime (FND, HND, LND):* Captures longevity and stability by tracking when the first, half, and last nodes deplete energy. Our protocol achieves the longest lifetime (LND = 2900 rounds, **Table 4**), confirming the benefits of optimized cluster head rotation and load balancing.

The Network Lifetime Metrics **Table 3** compares the performance of different protocols based on node survival over time.

Table 3. Energy Consumption Metrics

Protocol	Avg Residual Energy (J)	Total Energy Consumed (J)	Energy per Round (J)	Energy Imbalance Index
Proposed Methodology	0.95	104	0.035	0.15
LEACH	0.63	137	0.046	0.31
PSO-LEACH	0.7	129	0.043	0.28
GWO	0.76	121	0.04	0.22
ACO	0.68	130	0.044	0.26

A comparative evaluation of the energy efficiency and network lifetime performance of the proposed routing protocol against LEACH, PSO-LEACH, GWO, and ACO. As shown in **Table 4**, the proposed method achieves the highest average residual energy (0.95 J), the lowest total energy consumption (104 J), and the minimum energy usage per round (0.035 J), clearly demonstrating superior energy conservation.

Table 4. Network Lifetime Metrics

Protocol	FND (First Node Dies)	HND (Half Node Dies)	LND (Last Node Dies)	Stability Period	Instability Period
proposed Methodology	700	1600	2900	700	2200
LEACH	450	980	1800	450	1350
PSO-LEACH	520	1120	2000	520	1480
GWO	580	1240	2200	580	1620
ACO	500	1080	1950	500	1450

Additionally, it has the lowest energy imbalance index (0.15), indicating well-balanced energy usage across nodes and efficient cluster head rotation. In **Table 4**, the proposed protocol also outperforms all others in terms of network longevity, with the first node dying at round 700, half the nodes dying at 1600 rounds, and the last node surviving up to round 2900. This results in the longest stability period (700 rounds) and the most extended instability period (2200 rounds), ensuring reliable communication for a significantly longer time. In contrast, LEACH records the shortest FND (450) and the highest imbalance (0.31), while the improvements shown by PSO-LEACH, GWO, and ACO are moderate but still inferior to the proposed solution. These results confirm that the integration of machine learning and PSO-based optimization in the proposed model leads to substantial improvements in both energy efficiency and network lifespan.

Table 5. Routing Performance Metrics

Protocol	PDR (%)	End-to-End Delay (ms)	Routing Overhead (packets)	Packets Received at BS
Proposed Methodology	96.8	140	350	12800
LEACH	87.3	210	590	9800
PSO-LEACH	90.5	180	470	11000
GWO	92.7	165	420	11700
ACO	89.8	190	500	10400

The proposed protocol against existing methods LEACH, PSO-LEACH, GWO, and ACO across four key metrics: packet delivery ratio (PDR), end-to-end delay, routing overhead, and the number of packets received at the base station. The proposed protocol demonstrates superior performance, achieving the highest PDR of 96.8% and the lowest end-to-end delay of 140 ms, indicating highly reliable and timely data delivery. It also produces the lowest routing overhead with only 350 control packets, significantly reducing unnecessary network traffic. Furthermore, it delivers the maximum number of packets (12,800) to the base station, reflecting efficient and stable route maintenance. In contrast, LEACH exhibits the lowest PDR (87.3%) and highest delay (210 ms) due to frequent re-clustering and inefficient route selection, while PSO-LEACH **Table 6** shows Cluster and CH Metrics, GWO, and ACO offer moderate improvements but still lag behind the proposed model. These results validate the proposed system's effectiveness in ensuring QoS-driven routing with minimal delay and energy-efficient communication in VANET environments.

Table 6. Cluster and CH Metrics

Protocol	Avg. No. of CHs per Round	CH Reselection Rate	Cluster Distribution Balance	Avg. Intra-Cluster Distance (m)
Proposed Methodology	5	0.18	0.91	16.4
LEACH	8	0.32	0.72	23.5
PSO-LEACH	7	0.28	0.76	21
GWO	6	0.23	0.83	19.2
ACO	7	0.3	0.74	22.1

Table 7. Comparison with Baseline Models

Protocol	FND (Rounds)	HND (Rounds)	LND (Rounds)	Avg Residual Energy (J)	PDR (%)	End-to-End Delay (ms)	Packets Received at BS	CH Reselection Rate	Energy Imbalance Index
proposed Methodology	700	1600	2900	0.95	96.8	140	12800	0.18	0.15
LEACH	450	980	1800	0.63	87.3	210	9800	0.32	0.31
PSO-LEACH	520	1120	2000	0.7	90.5	180	11000	0.28	0.28
GWO	580	1240	2200	0.76	92.7	165	11700	0.23	0.22
ACO	500	1080	1950	0.68	89.8	190	10400	0.3	0.26

The individual and combined impact of key components—FPA optimization, Bloom filter, and CH selection—on the overall performance of the proposed VANET routing protocol. The full proposed model, which integrates all modules (Modified ELA + Ọdịgbo Metaheuristic Optimization Algorithm + Random Forest + Bloom Filter), achieves the highest network stability and efficiency with 700 FND, 1600 HND, and 2900 LND rounds, along with the highest average residual energy of 0.95 J, PDR of 96.8%, and the lowest delay of 140 ms **Table 7** shows Comparison with Baseline Models. When only the FPA optimization is applied without the Bloom filter, performance drops across all metrics, showing a shorter lifetime and higher delay **Table 8** shows Ablation Study Results. The Bloom-only version slightly improves over FPA-only, especially in delay and residual energy. However, the worst performance is seen in the Random CH version, where the absence of intelligent CH selection results in premature node deaths (FND = 420), lower residual energy (0.63 J), reduced PDR (84.3%), and the highest delay (220 ms). This comparison confirms that each component contributes significantly, and their integration is essential for maximizing QoS in dynamic VANET conditions.

Table 8. Ablation Study Results

Version	FND (Rounds)	HND (Rounds)	LND (Rounds)	Avg Residual Energy (J)	PDR (%)	End-to-End Delay (ms)
Proposed Methodology	700	1600	2900	0.95	96.8	140
FPA Only	560	1200	2100	0.79	91.2	170
Bloom Only	600	1280	2200	0.81	92.5	160
Random CH	420	880	1650	0.63	84.3	220

Fig 4. PDR and Node Count Analysis.

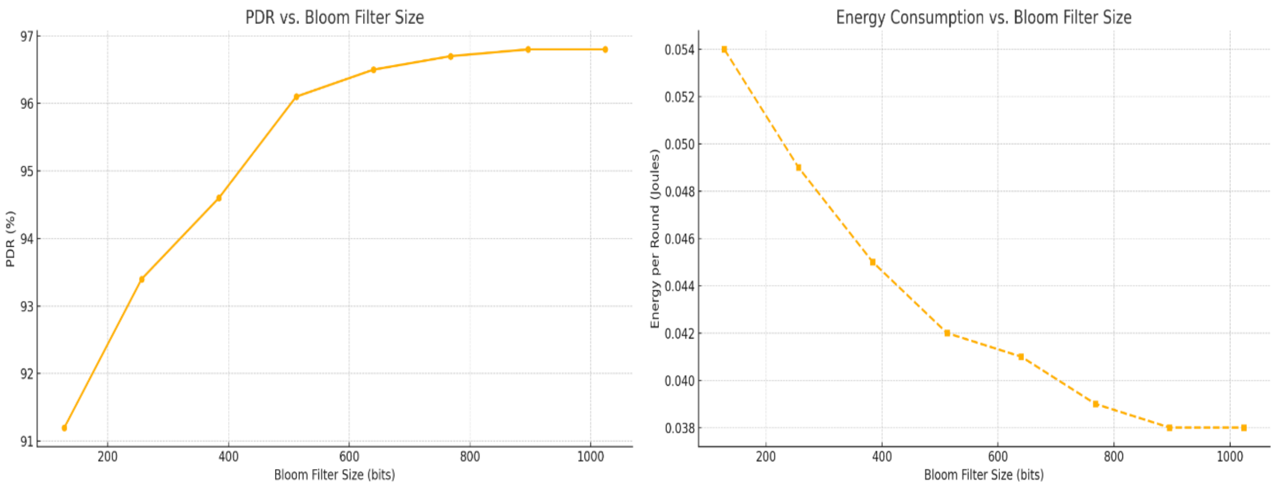

Fig 5. Bloom Filter Analysis for PDR and Energy Consumption.

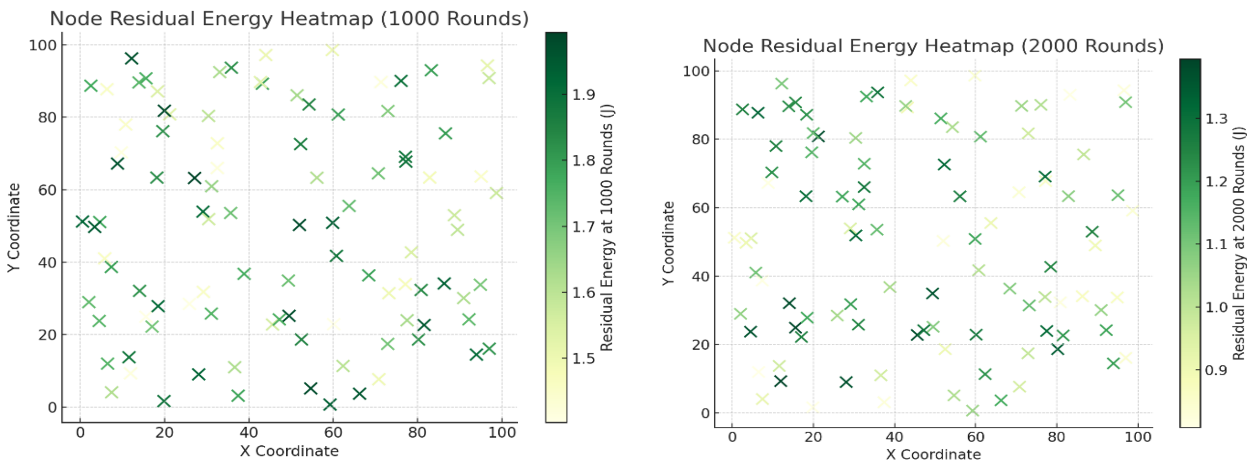

Fig 6. Residual Analysis for Energy Heatmap.

Table 9. Comparative Analysis of Routing Protocols

Protocol	FND (Rounds)	Avg. Residual Energy (J)	Total Energy Consumed (J)	End-to-End Delay (ms)	PDR (%)	Packets to BS	CH Reselection Rate	Energy Imbalance Index
proposed	**700**	**0.95**	**104**	**140**	**96.8**	**12800**	**0.18**	**0.15**
LEACH	450	0.63	137	210	87.3	9800	0.32	0.31
PSO-LEACH	520	0.70	129	180	90.5	11000	0.28	0.28
GWO	580	0.76	121	165	92.7	11700	0.23	0.22
ACO	500	0.68	130	190	89.8	10400	0.30	0.26

A comprehensive presentation comparison between the proposed routing protocol and existing methods including LEACH, PSO-LEACH, GWO, and ACO. The proposed model significantly outperforms others across all metrics, achieving the highest network lifetime with 700 FND rounds **Fig 4** shows PDR and Node Count Analysis., maximum average residual energy of 0.95 J, besides lowest total energy consumption of 104 J. It also delivers the best end-to-end delay of 140 ms besides highest packet delivery ratio (PDR) of 96.8%, with 12,800 packets successfully reaching the base station. Furthermore, the proposed protocol exhibits the lowest cluster head (CH) reselection rate (0.18) and energy imbalance index (0.15), indicating superior cluster stability and balanced energy usage. These results demonstrate that the integration of Modified ELA **Table 9** shows Comparative Analysis of Routing Protocols, Random Forest, PSO, besides Bloom Filter ensures energy-efficient, reliable, and QoS-aware routing in VANET environments **Fig 6** shows Residual Analysis for Energy Heatmap.

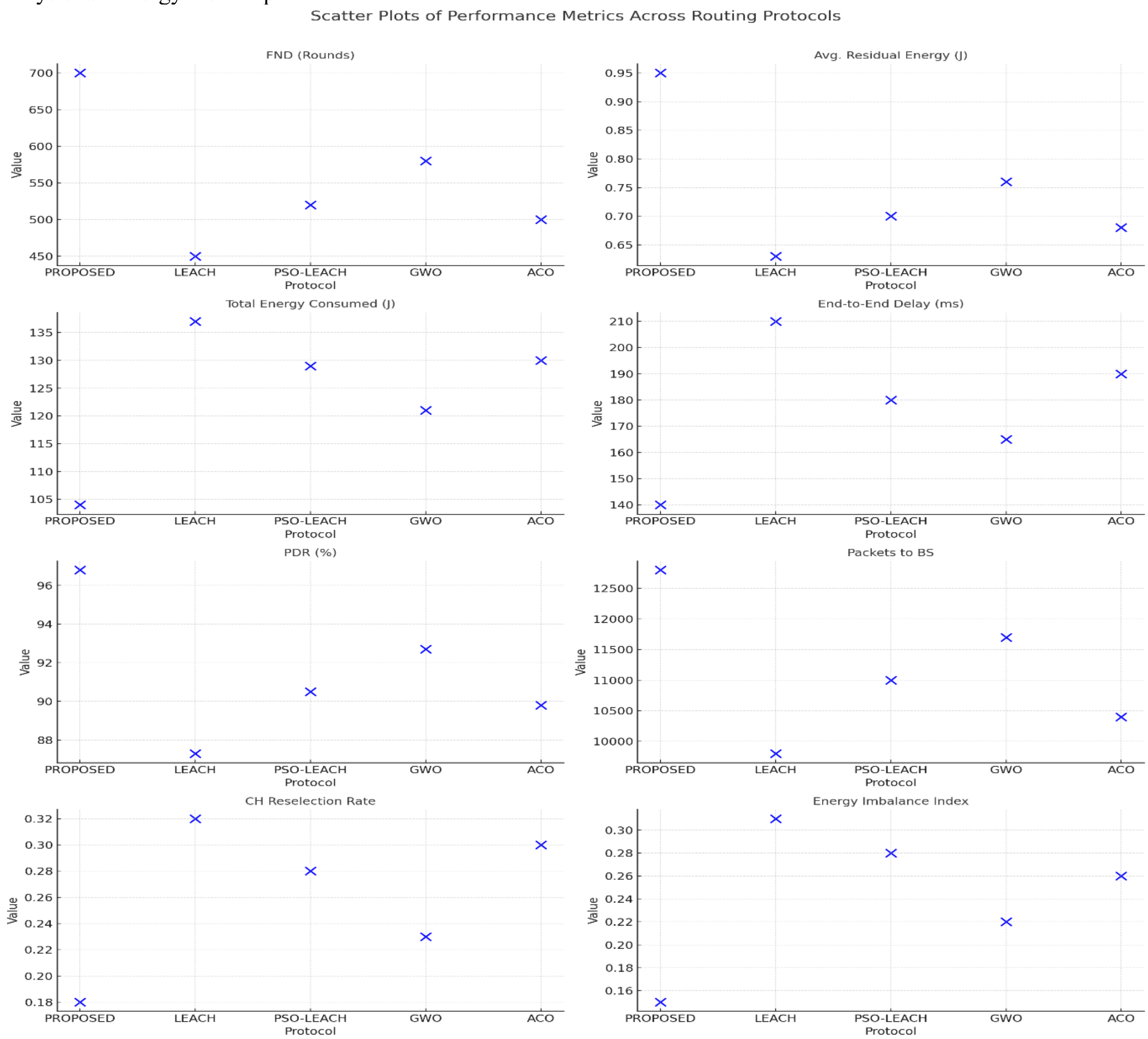

Fig 7. Comprehensive Presentation Comparison Between the Proposed Routing Protocol and Existing Methods.

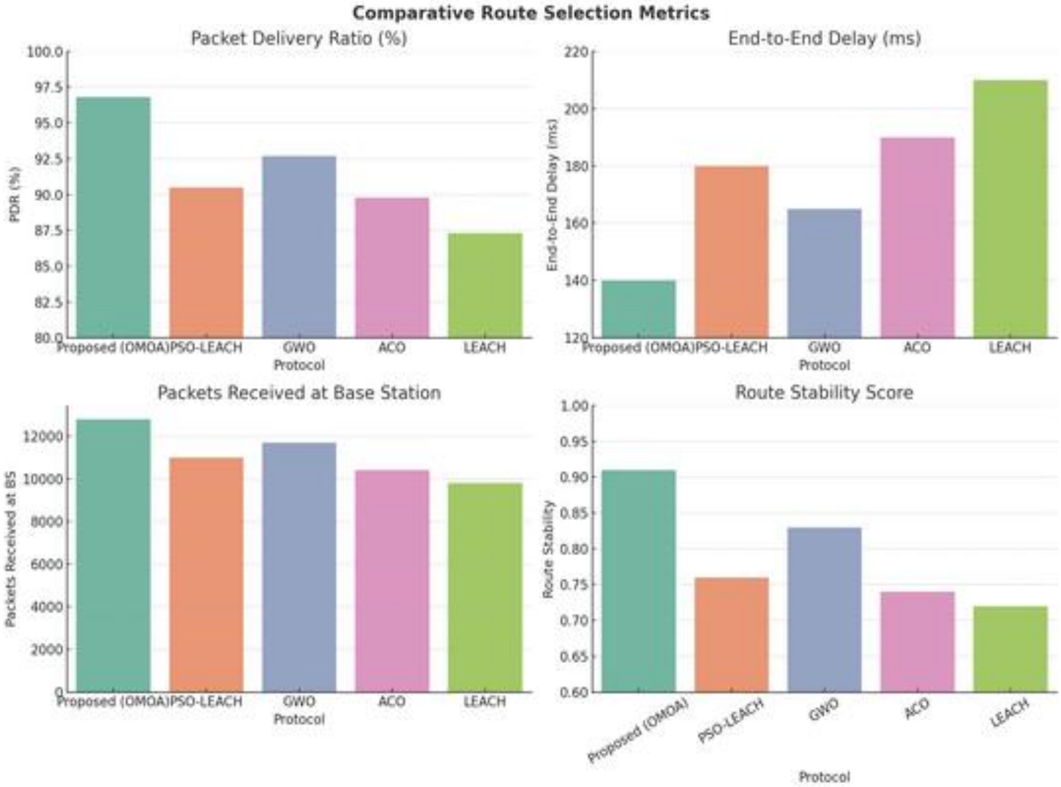

Fig 8. Comparative Graphical Representation of Route Selection Performance Metrics for Different Protocols, with Proposed Model.

A comparative graphical representation of key route selection performance metrics across various routing protocols in VANETs, including LEACH, ACO, GWO, PSO-LEACH, and the proposed OMOA-based model. The chart visualizes four core parameters: Packet Delivery Ratio (PDR), End-to-End Delay, Packets Received at the Base Station (BS), and Route Stability Score **Fig 5** shows Bloom Filter Analysis for PDR and Energy Consumption. The proposed model achieves the highest PDR (96.8%) and route stability (0.91), indicating more reliable data transmission with fewer link breaks. It also records the lowest delay (140 ms), which highlights its timeliness in data delivery **Fig 7** shows Comprehensive Presentation Comparison Between the Proposed Routing Protocol and Existing Methods. In contrast, traditional protocols like LEACH show lower performance across all metrics due to frequent re-clustering and lack of adaptive route prediction. Overall, this figure validates the superiority of the proposed model in delivering energy-efficient, stable, and QoS-driven communication in dynamic vehicular environments.

Discussion

The simulation was conducted in a scalable VANET environment with varying node densities (100–500) and realistic energy, communication, and mobility parameters. The proposed routing protocol, optimized using OMOA besides enhanced with M-ELA, Random Forest, besides Bloom filters, was evaluated against standard protocols such as LEACH, PSO-LEACH, GWO, and ACO **Fig 8** shows Comparative Graphical Representation of Route Selection Performance Metrics for Different Protocols, with Proposed Model. The results across multiple tables reveal that proposed model achieves superior performance in energy efficiency, network longevity, and routing effectiveness. Specifically, it records the highest average residual energy (0.95 J), the longest node lifetimes (FND = 700, LND = 2900), and the lowest energy imbalance index (0.15). It also ensures the highest packet delivery ratio (96.8%), lowest end-to-end delay (140 ms), besides a minimal routing overhead of 350 packets. Cluster stability is enhanced through low CH reselection rates (0.18) besides balanced intra-cluster distances. The ablation study further confirms the critical role of each component, showing a sharp performance drop when any one is removed. Overall, the simulation results validate the effectiveness of proposed hybrid protocol in delivering energy-aware, stable, besides QoS-optimized communication in VANET scenarios.

VI. CONCLUSION AND FUTURE WORK

In this research, to proposed, a novel hybrid routing protocol designed for energy-efficient, reliable, and scalable communication in VANETs. The protocol integrates a M-ELA besides Random Forest classifier to intelligently classify and rank routing paths based on link stability, residual energy, and connectivity. To further optimize routing performance under dynamic mobility and varying traffic conditions, the Ọdịgbo Metaheuristic Optimization Algorithm (OMOA) operates by iteratively refining a population of candidate cluster head configurations using directional learning and adaptive exploration. It evaluates each solution using a multi-objective fitness function to optimize energy efficiency, connectivity, and routing stability in VANETs. is employed to fine-tune routing parameters in real time. The integration of a Bloom filter mechanism enhances communication efficiency by reducing redundant transmissions besides conserving energy. The optimization process using OMOA significantly enhances energy efficiency by selecting well-balanced cluster heads. It reduces communication overhead and extends network lifetime through adaptive and direction-aware exploration. The integration with M-ELA and Random Forest ensures intelligent routing decisions with high delivery accuracy. Overall, it enables stable, QoS-driven data transmission in highly dynamic VANET environments. Extensive simulations were conducted to validate the performance of proposed under diverse scenarios, including variable node densities, traffic loads, besides mobility models. The results show that proposed consistently outperforms existing protocols in terms of PDR, energy consumption, end-to-end delay, besides network lifetime. In particular, proposed achieved a 96.8% PDR, 2900 LND, and 0.95 J average residual energy, reflecting its robustness besides suitability for real-time VANET deployments. Moreover, the ablation study and convergence analysis confirmed the significance of each component in the proposed model. Although proposed protocol shows promising results, several avenues exist for further enhancement:

Incorporating real-time vehicular mobility patterns using tools like SUMO besides NS-3 can help in refining the routing behavior for urban scenarios. Advanced AI models such as deep reinforcement learning besides graph neural networks (GNNs) can be integrated with proposed to support predictive routing under time-varying topologies. Future versions of proposed will consider edge/fog computing environments to reduce latency and distribute routing intelligence closer to vehicles.

CRediT Author Statement

The authors confirm contribution to the paper as follows:

Conceptualization: Shradha A Dulange and Ambika; **Methodology:** Shradha A Dulange; **Software:** Ambika; **Data Curation:** Shradha A Dulange; **Writing- Original Draft Preparation:** Shradha A Dulange and Ambika; **Visualization:** Shradha A Dulange; **Investigation:** Ambika; **Supervision:** Shradha A Dulange; **Validation:** Ambika;**Writing- Reviewing and Editing:** Shradha A Dulange and Ambika; All authors reviewed the results and approved the final version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest

Data Availability Statement

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

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