International Journal of Engineering Trends and Technology
ISSN: 2231-5381/ https://doi.org/10.14445/22315381/IJETT-V74I8P119
Volume 74 Issue 8, 278-293, August 2026

Original Article

Intelligent Cluster Head Selection and Aquila Optimizer Based Multi-Objective Routing (AOMOR) Protocol with Digital Twin Simulation for VANET

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Received: 03 March 2026 Revised: 11 July 2026 Accepted: 22 July 2026 Published: 29 August 2026

Abstract - *The next-generation Intelligent Transportation Systems (ITS) use Vehicular Ad Hoc Networks. This facilitates real-time vehicle-roadside infrastructure communication. However, maintaining stable cluster topologies and guaranteeing consistent Quality of Service is problematic because of VANETs intrinsic high mobility and adaptable topology. In this paper, proposed a Self-Adaptive Marine Predators Algorithm (SAMPA) with an Aquila Optimizer-based Multi-Objective Routing (AOMOR) strategy for Cluster Head Selection (CHS). Instead of demanding all nodes to maintaining links over the entire network, the local interactions among clusters facilitates in lowering the routing complexity. SAMPA, a nature-inspired metaheuristic algorithm, models the foraging strategies of marine predators in their search for prey. It is employed here to select the most suitable CHs by solving a Multi-Objective Optimization (MOO) problem that balances key metrics, including Node Density (ND), Residual Energy (RE), mobility, Link Quality (LQ), and Connectivity Degree (CD). For the routing process, AOMOR employs the hunting strategies of Aquila (eagle) species, which ivolnve searching, swooping, and attacking behaviors, to determine the optimal communication path. Mean Routing Load (MRL), Packet Delivery Ratio (PDR), throughput, End-to-End (E2E) delay, and Control Packet Overhead (CPO) represent several of the objectives, are taken into account by QoS-aware routing. To further enhance adaptability, the Digital Twin technology is integrated in the suggested method, which facilitates real-time analysis of network activities, traffic prediction, and informed decision-making for routing strategies. Proposed structure in improving the efficiency of CHS and improving QoS provisioning in VANETs are demonstrated by evaluating its performance using important metrics such as PDR, Packet Loss Ratio (PLR), E2E delay, throughput, and Average Residual Energy (ARE).*

Keywords - *VANET, Self-Adaptive Marine Predators Algorithm (SAMPA), Aquila Optimizer (AO), Optimal CH selection, Routing, Clustering, Digital twin, and Optimized framework.*

1. Introduction

Vehicular Ad hoc Networks are a foundational part in Intelligent Transportation Systems with a capability to facilitate the sharing of safety, traffic and infotainment information among vehicles in highly dynamic road settings. The major modalities of communication, VANET communication is supported by Infrastructure-to-Vehicle (I2V), Vehicle-to-Vehicle (V2V), and Vehicle-to-Infrastructure (V2I). Wireless Access in Vehicular Environments (WAVE) uses Dedicated Short-Range Communication (DSRC) in the 5.9 GHz band to provide low-latency short-range communication for safety-critical applications [1, 2]. The IEEE 802.11p and IEEE 1609 standards specify physical, MAC, and higher-layer protocols required for reliable vehicle communication. Moreover, LTE and 5G technologies are widely used to provide wide area coverage, greater data rates and infrastructure-supported services, such as traffic monitoring, cloud-assisted driving and entertainment applications.

Figure 1 depicts a typical VANET setup where vehicles connect directly with neighbouring vehicles via V2V links and with roadside infrastructure through V2I/I2V links.

DSRC/WAVE is good for short-range and delay-sensitive message exchange, and LTE/5 G offers larger communication coverage and enhanced ITS services. The integration of DSRC, LTE and 5G enhances VANET connection, but also brings new issues for routing, congestion control, resource allocation and quality of service management [3].

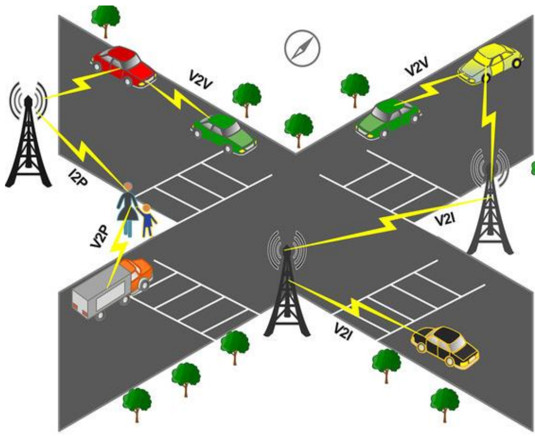

Fig. 1 A typical VANET scenario

Although VANETs have many advantages, reliable communication is problematic because to the important vehicle mobility and frequent topology changes, different node density, and limited spectral resources [4, 5]. A large number of broadcast safety warnings in dense traffic conditions may cause channel congestion, packet loss, hidden node trouble and end-to-end latency. In sparse traffic conditions, unreliable networks and intermittent connectivity decrease routing reliability [6, 7]. For example, many traditional routing and clustering approaches are incapable of efficiently adapting to such dynamic settings since they generally use static parameters, decision rules or single-objective optimization [8, 9]. Thus, they may not always provide stable cluster-head selection, effective gateway detection, and QoS-aware routing in the dynamic VANET environment.

Existing studies have employed clustering strategies to improve scalability and coordination in VANETs. In clustering-based VANET communication, the vehicles are classified into clusters based on the criteria including vehicle density, speed, direction, link stability and geographic position [10]. A Cluster Head (CH) is picked to handle intra-cluster communication, to reduce duplicated message transmission, to handle medium access and to promote effective safety-message distribution [11]. However, clustering enhances the organization of the network, but many existing CH selection methods do not simultaneously address several objectives such as node stability, traffic density, communication delay, connection reliability and routing efficiency. Similarly, many routing protocols are focused exclusively on using the shortest path or connectivity, and ignoring QoS limitations and resource optimization in real-time.

Recently, meta-heuristic optimization techniques have been given importance for routing and VANET clustering because of their ability to identify nearly optimal solutions in challenging and changing environments [12]. Routing, load balancing and resource allocation problems have been tackled successfully using algorithms that emulate natural behaviors, such as swarm intelligence, predator-prey mechanisms and evolutionary search. However, many existing optimization-based VANET techniques still have drawbacks. Firstly, many research optimize the CH selection or routing individually instead of concurrently solving the two challenges. Secondly, the selection of gateway nodes that are critical for stable inter-cluster communication is generally not discussed in detail [13]. Third, most of the approaches do not provide a Digital Twin-based modeling environment to assess clustering and routing decisions before applying to the real VANET. These restrictions provide a research gap for an adaptive multi-objective and simulation-assisted VANET communication framework.

To address this gap, this research proposes an Aquila Optimizer-based Multi-Objective Routing strategy integrated with a Self-Adaptive Marine Predators Algorithm for effective VANET communication. The Self-Adaptive Marine Predators Algorithm is used for stable and energy-efficient CH selection by taking into account significant vehicular aspects like as node mobility, link quality, traffic density, and cluster stability. Then, the ideal routing path is found by applying the exploration and exploitation mechanism of the Aquila Optimizer based on the hunting behavior of the Aquila species. Moreover, to simulate the clustering and route selection procedures before the final decision, a Digital Twin model of the VANET environment is utilized. This increases adaptability, dependability and scalability of the suggested system.

The proposed research is innovative as it combines SAMPA-based CH selection with Aquila Optimizer-based multi-objective routing, gateway node identification, and Digital Twin-assisted VANET simulation. The suggested framework differs from traditional clustering or routing methods that seek to optimize a single objective. In the proposed framework, cluster stability, routing efficiency, QoS performance, and resource consumption are all improved simultaneously. Hence, the suggested approach is predicted to decrease the packet loss, improve data delivery, decrease the communication delay and increase the overall reliability of VANET operations in dynamic traffic scenarios.

2. Literature Review

Improved Hybrid Ant Particle Optimisation (IHAPO) is introduced to reduce travel time with smart transportation by Jindal and Bedi [14]. By avoiding the best route when it is crowded and returning to it when it becomes less congested, the IHAPO algorithm chooses the best route during peak hours. By integrating it with the Particle Swarm Optimisation (PSO), this method enhances the Modified Ant Colony Optimisation (MACO) algorithm. At first, every technique operates independently and generates its optimal results. In the entire network, a novel global best solution has been identified by comparing two solutions. Ant and particle positions are adjusted for subsequent iterations based on the optimal solution found. The IHAPO algorithm is used for standard road conditions. All roads are assumed to be in normal operating condition for the MACO algorithm to function. The Simulation of Urban MObility (SUMO) simulator is simulated based on a North-west Delhi map.

Yasir Ali Shah et al. [15] proposed a Moth-Flame Optimization (CAMONET)-based clustering algorithm for VANETs, clusters are created and optimised for reliable transmission. CAMONET is empirically evaluated using other techniques, including MOPSO, the Comprehensive Learning Particle Swarm Optimization (CL-PSO) and ACO-based clustering technique for VANETs. By altering the network grid size, node count, and node transmission range, the desired outcomes are achieved by proposed model. The key elements for optimal clustering are the nodes speed, direction, and transmission range. CAMONET provides nearly ideal outcomes, making it an effective technique for performing vehicular clustering to enhance the overall performance of system.

Christy Jackson Joshua et al. [16] suggested a method for VANETs termed Reputation-based Weighted Clustering Protocol (RWCP). To stabilise the VANET topology, RWCP frames the consideration of vehicle path, place, speed, count of neighboring vehicles, path ID, and reliability of every node. On the other hand, optimising becomes difficult when dealing with different RWCP control parameters. In order to provide improved cluster longevity, improved PDR, and decreased cluster overhead, multi-Objective problem that accepts the RWCP parameters as input. RWCP parameters are optimised using the evolutionary Multi-Objective Firefly Algorithm (MOFA). The MOFA framework and the TETCOS NetSim simulator were used for simulations. Mean Cluster Lifetime, PDR, and CPOmetrics are evaluated with the suggested approach.MOPSO and CL-PSO were used to compare the outcomes of experiments using realistic maps from OpenStreet Maps.

Gnanasekar and Samiappan [17] presented innovative VANET routing model. The cost related to traffic, collision, path, and QoS needs are considered by this novel technique. The fuzzification of the QoS element is also included. Cuckoo Search (CS) and Rider Optimization Algorithm (ROA) integration, such as Rider Integrated Cuckoo Search (RI-CS), allows for choosing best path with the lowest routing expenses. Additional models include Mean Computing Jaya Algorithm (MC-JA), PSO, FA, Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WAO), ROA, CS, and Grey Updated Butterfly Operator (GU-BO), are compared to the RI-CS method in terms of particular cost analysis.

Rashid et al. [18] provided VANET routing based on Reliability Aware Multi-Objective Optimization (RAMO). The VANET system simulation is the first level; the routing criteria, which are based on geometrics, dependability, are second; and the routing algorithm is third, followed by real network implementation. Additionally, each reliability, geometrical, and routing block's parameters are controlled by an optimization block included in the framework. The optimization is based on the development of a new version of multi-objective harmony, aiming for and is given under the multi-objective perspective. Gaussian mutation, objective decomposition, and a harmony memory extraction approach are all included in the introduction of Enhanced Gaussian Mutation Harmony Searching (EGMHS). Initially, nine benchmarking mathematical functions were used to evaluate the EGMHS. Network simulation research that evaluated EGMHS in comparison to RAMO was the second RAMO assessment. The metrics acquired, such as set coverage, delta metric, hyper-volume, PDR, and End-To-End (E2E) latency, show that EGMHS and RAMO with EGMHS are superior to other techniques.

Husnain et al. [19] proposed a probability-based and nature-inspired WOA (p-WOA), a bio-inspired, cluster-based routing algorithm. In terms of vehicle communication, it produces cluster formation. Randomness was reduced by considering a variety of parameters and including their probabilities into the fitness function, such as highway route, velocity, node count, and communication range. The proposed p-WOA strategy generates an optimal amount of CH when compared to current methods like Ant Lion Optimiser (ALO) and GWO. PDR, average throughput, and latency are used to measure the results, and show better the suggested approach is than other conventional methods (ALO and Grey Wolf Optimization (GWO)).

Badole and Thakare [20] proposed a hybrid optimisation model that includes optimal CHS for data transmission. CHS process, including MRL, PDR, throughput, E2E Delay (E2ED), and CPO. Hunger Foraging Behaviour Customised Honey Badger Optimisation (HFCHBO) is presented to identify the optimal CH from a pool of possible candidates. Hunger Games Search (HGS) and the Honey Badger Algorithm (HBA) are combined in the HFCHBO. Effective data transmission routing routes between vehicles and DT among the CH to the BS are made possible by this hybrid model. In order to provide consistent performance in dynamic contexts, the HFCHBO model attempts to address the drawbacks of conventional clustering methods by combining these two strategies. The performance of possible CHs in the clustering is assessed using a number of objectives and the route selection mechanism. This HFCHBO structure facilitates data transfer between vehicles and the CH to the BS, as it creates effective routing channels. The network behaviour is analysed, traffic patterns are predicted, and well-informed routing strategy decisions by the model using the Digital Twin technology.

Maria Christina Blessy [21] proposed optimising the CHS process, a novel Intelligent Fuzzy Bald Eagle (IFBE) optimisation method. This suggested model enhances the ability of VANET. The suggested approach makes use of the intelligent fuzzy system, and it optimizes the CHS process. Fuzzy rules and Membership Functions (MFs)are utilized to determine whether a candidate node is suitable to serve as CH. The best values for the MF are then found using the metaheuristic technique known as Bald Eagle Search (BES) optimisation. MATrix LABoratory (MATLAB) was used to evaluate the suggested mechanism. In terms of energy usage, E2ED, and PDR, the IFBE approach surpasses other existing systems.

Self-Healing Routing approach with the Ant Colony Optimization (SHR-ACO) was suggested by Jianhang Liu et al. [22]. ACO algorithm is implemented to create routing paths with guarantee connectivity and immediacy. A vehicle's forwarding capability is measured by the Routing-Build-Ability (RBA). To lessen the complexity of computation, the RBA is obtained by using the fuzzy logic system to analyse the packet PDR and latency. In-road-repairing and intersection-repairing techniques are suggested to decrease the overhead of route reconstruction caused by path disconnection. These techniques increase T and extend the optimal path's duration. The mathematical analyses and simulation results show that the feasible SR can increase the T by three times, promote the routing duration by three times, decrease the time overhead to one sixth, and reduce the latency by thirty percent.

Krishna Meera et al. [23] to determine the optimal number of vehicle node clusters, the Hybrid Hippopotamus Optimization Algorithm Stable Cluster Construction Protocol (HHPOASCCP) was proposed. HHPOASCCP is based on the Hybrid Hippopotamus Optimisation Algorithm. To avoid the issue of local optima and find a globally optimal solution that denotes ideal vehicle clusters, the intrinsic factors of HPOA assisted in preserving a suitable equilibrium among the steps of Exploration and Exploitation (E-E). In order to maximise the energy efficiency, this suggested clustering technique identified the ideal number of clusters and highly suitable vehicular nodes as CH. HHPOASCCP approach with lowered energy consumption by 19.84%, increased load balancing by 23.12% and reduced the number of clusters by 24.58%, and confirmed that 24.38% of the nodes were chosen as CH.

2.1. Research Gap

It identifies several improvements in VANET clustering and routing through SAMPA-based Cluster Head Selection, AOMOR routing, and Digital Twin integration. However, a significant research gap remains in the lack of comprehensive validation under highly dynamic real-world vehicular environments involving heterogeneous traffic densities, varying road conditions, and large-scale urban scenarios. Although the proposed framework optimizes cluster stability, QoS metrics, and routing efficiency, it does not sufficiently address security threats such as malicious vehicle behavior, false information dissemination, and cyber-attacks that can affect routing reliability. Furthermore, the Digital Twin component is primarily utilized for traffic prediction and network monitoring, while its potential for real-time adaptive decision-making, anomaly detection, and predictive network self-healing is not fully explored. The study also lacks evaluation of computational complexity, scalability for ultra-dense VANET deployments, and interoperability with emerging 5G/6G-enabled intelligent transportation systems, creating opportunities for future research toward more secure, scalable, and intelligent VANET architectures.

3. Proposed Methodology

In this paper, novel QoS-driven routing is introduced using an Aquila Optimizer (AO) and Cluster Head (CH) selection using the Self-Adaptive Marine Predators Algorithm (SAMPA). The network is simplified by clustering vehicle types so they may communicate largely with other vehicles in their clusters rather than all at once. A novel MH optimisation algorithm inspired by nature is called SAMPA. By choosing the best node to serve as the CH, this SAMPA imitates the foraging techniques used by marine predators in the ocean to find prey. QoS-aware routing process is based on the AO with the hunting strategies of the Aquila (eagle) species, which use different searching, swooping, and attacking techniques for optimal path selection. The proposed method uses digital twin technologies to predict traffic patterns, assess network activity, and make well-informed routing strategy selections.

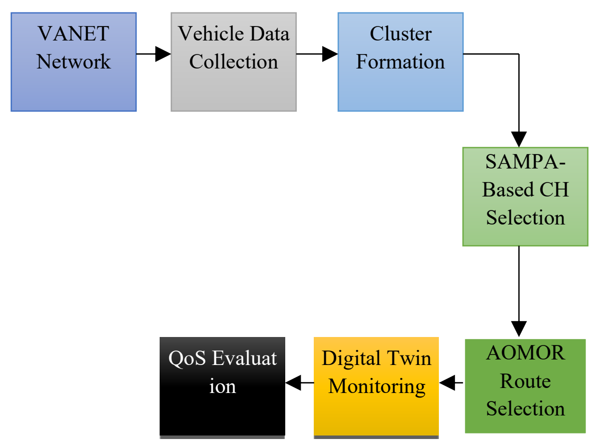

Fig. 2 Block diagram of the proposed qos-aware vanet routing framework

The block diagram illustrated that the proposed SAMPA-AOMOR framework linked with Digital Twin technology for VANETs is shown in Figure 2. First of all, the VANET Network comprises of the vehicles talking with each other and the roadside infrastructure. Important data, including vehicle position, speed, mobility, connection, and link quality, is obtained during the Vehicle Data Collection stage. By these parameters, Cluster Formation is done to combine the vehicles into manageable clusters to increase network scalability and reduce communication overhead. Then, the SAMPA-Based Cluster Head Selection module chooses the best Cluster Heads by maximizing parameters such as node density, residual energy, mobility, connection quality, and degree of connectivity. The selected Cluster Heads then engage in the AOMOR Route Selection process, where optimal communication channels are identified according to multi-objective routing criteria. The intelligent routing decisions are allowed by the Digital Twin Monitoring module, which continuously examines the behavior of the network and traffic situations. Finally, the QoS Evaluation stage examines the network performance using measures including packet delivery ratio, latency, throughput, packet loss, and residual energy to guarantee efficient and reliable communication.

3.1. Vanet Structure

A digital twin of the real network is part of the VANET architecture. A network of highways measuring 100*100 has been built. The N vehicles are within the dimensions. Every single vehicle has been going at a constant speed of 30 km/h and has been dynamic. Every vehicle has a distinct ID. They also have a place to find out where it is right now. The RSU communication range is the same in each lane. IEEE 802.11p-compliant radio transceiver is used to communicate between the RSU and the network's vehicles. In order to effectively control traffic, each vehicle usually exchanges information about its geographic vicinity. Clusters are crucial logical entities for effective resource allocation and resource management in VANETs. In order to facilitate efficient data dissemination, clusters are frequently used. Instead of sending data over a network, data is transmitted within a particular cluster. The overall performance of VANET applications may be compromised, and ineffective utilisation of resources may result from clusters that lack stability or cohesion.

3.2. Clustering Mechanism

Vehicles can now primarily interact with other vehicles inside their particular groups instead of forming direct links with every vehicle due to clustering, which reduces the overall complexity of the network by splitting it up into clusters. Maintaining reliable clustering becomes crucial to maintaining system adaptability and manageability as vehicle volume and traffic density rise. Reliable clustering can be achieved by precisely predicting and modelling vehicle movements within clusters. Based on a number of parameters, nodes are grouped in a single cluster. The primary goal of a vehicle cluster is to enable communication amongst vehicles. CHs are selected for controlling the whole cluster in each cluster. The interaction between and within clusters is the responsibility of CH. Because of the lower communication overhead, a network that has fewer clusters is usually less expensive. The longevity of each cluster is directly related to the structure efficiency. According to the MO, the best CH is chosen for this study. A new SAMPA is used to select the best CH. The MOO problem is introduced, which balances key metrics including ND, RE, mobility, LQ, and CD. Each vehicle could be in one of four states according to the suggested cluster algorithm,

(i) Initial node (IN): Vehicles that are not part of any cluster in their initial state.
(ii) CH: the state where the vehicle leads a cluster of vehicles.
(iii) CM: The state of the vehicle attachment to the current CH.
(iv) Candidate Cluster Member (CCM): Before getting a confirmation message, the vehicle is in the state where it plans to be a CM of a current cluster.

To ensure dependable connectivity for a collection of vehicles, suggest a clustered VANET architecture. The fundamental system architecture for vehicular service scenarios with many moving clusters of vehicles is shown in Figure 3. A Capital Vehicle (CH) is present in each cluster. Data pertaining to the CM and DT must be maintained by a captive vehicle CH.

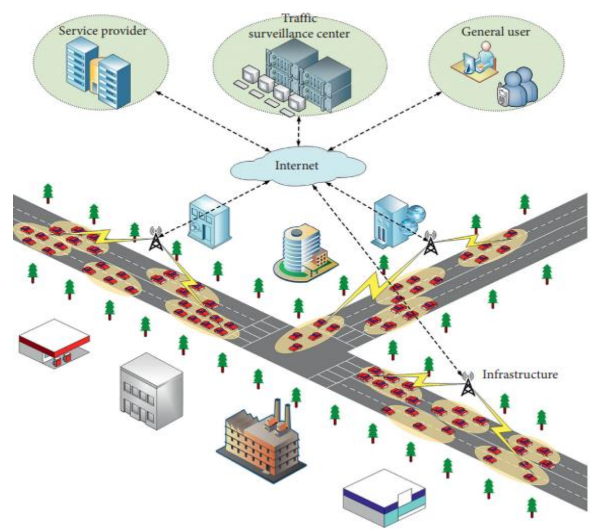

Fig. 3 Cluster based vanet design for vehicular service scenarios [24]

Cluster formation, cluster maintenance, and CHS make up the three key components of the suggested clustering strategy.

The Figure 4 depicts the operation sequence of the proposed Digital Twin-assisted SAMPA-AOMOR framework for VANETs. The first step is the VANET environment initialization, when the vehicles and the communication parameters are set. Then the vehicle information, such as position, speed, mobility, connectivity and link quality, is collected to get the current network state. Vehicles are grouped according to these factors to save communication overhead and improve network scalability. Then, the Self-Adaptive Marine Predators Algorithm (SAMPA) is applied to pick the best Cluster Heads by optimizing multiple criteria related to network stability and connectivity. After the selection of the Cluster Head, the best communication pathways between source and destination cars are obtained using the Aquila Optimizer-based Multi-Objective Routing (AOMOR) algorithm. The Digital Twin module constantly observes network conditions and traffic behavior for making intelligent routing decisions. Finally, to ensure dependable and effective vehicular communication, the network performance is assessed using Quality of Service (QoS) measures, including packet delivery ratio, latency, throughput, packet loss, and residual energy.

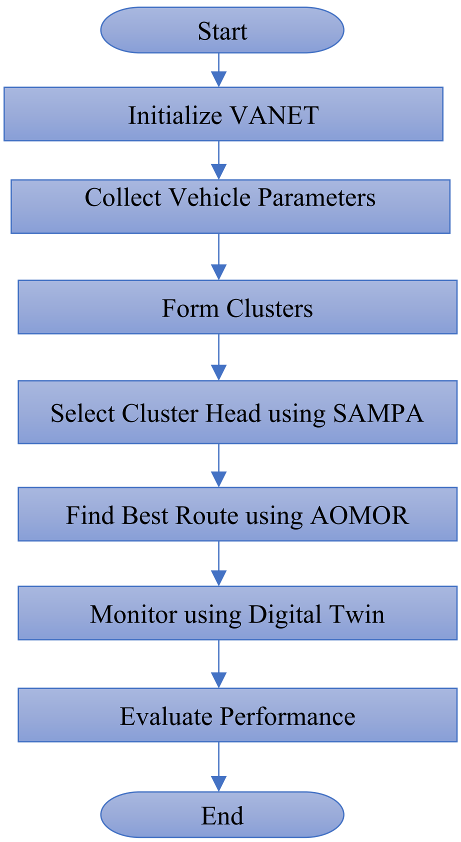

Fig. 4 Flow chart of the proposed work

3.2.1. Multi-Objective Optimization (MOO)

CHs by solving an MOO problem that balances key metrics, including Node Density (ND), Residual Energy (RE), Mobility (Mo), Link Quality (LQ), and Connectivity Degree (CD). For each candidate node, compute the normalized objective vector (all objectives minimized),

$$F(i) = (f_1(i), f_2(i), f_3(i), f_4(i), f_5(i)) \quad (1)$$

$$f_1(i) = \frac{|ND_i - ND_{opt}|}{ND_{opt}} \quad (2)$$

$$f_2(i) = \frac{RE_{max} - RE_i}{RE_{max}} \quad (3)$$

$$f_3(i) = \frac{Mo_i}{Mo_{Max}} \quad (4)$$

$$f_4(i) = \frac{1}{\epsilon + \frac{LQ_i}{LQ_{max}}} \quad (5)$$

$$f_5(i) = \frac{1}{\epsilon + \frac{CD_i}{CD_{max}}} \quad (6)$$

Where $\epsilon>0$ prevents division by zero; normalization constants may be rolling maxima or design bounds. Use a weighted sum when a single score is preferred by Equation (7),

$$C(i) = \sum_{k=1}^{5} w_k f_k(i) \quad (7)$$

then pick $i^* = \underset{i}{\operatorname{argmin}}\, C(i)$. Tune w_k to reflect application priorities (e.g., energy-sensitive vs. stability-sensitive).

Node Density (ND): ND measures how many neighbors a node has within its communication range R by Equation (8),

$$ND_i = \frac{|N_i|}{N_{max}} \quad (8)$$

Where N_i = number of neighbors of node i within R, N_{max}= maximum neighbor count in the network

Residual Energy (RE): RE is denoted as the ratio of remaining battery energy to maximum capacity. It is described by Equation (9),

$$RE_i = \frac{E_i}{E_{max}} \quad (9)$$

Here E_i= current RE of node i, E_{max}= initial or maximum battery capacity.

Mobility (Mo): Average relative speed of a node compared to its neighbors, over a time window *T*. It is described by Equation (10),

$$Mo_i = \frac{1}{|N_i|} \sum_{j \in N_i} \frac{|v_i - v_j|}{v_{max}} \quad (10)$$

Where v_i, v_j = velocities of nodes *i* and *j*, v_{max}= maximum observed speed (normalization).

Link Quality (LQ): Link quality is often measured by the percentage of correctly received data packets, indicating how reliably data is transmitted and received in the network model. It is described by Equation (11),

$$LQ_i = \frac{1}{|N_i|} \sum_{j \in N_i} PDR \quad (11)$$

Connectivity Degree (CD): Fraction of reliable neighbors (neighbors with acceptable link quality ≥τ). It is described by Equation (12),

$$CD_i = \frac{|\{j \in N_i | LQ_{ij} \geq \tau\}|}{N_{max}} \quad (12)$$

Where τ is denoted as the minimum acceptable link quality threshold (e.g., 0.7 PDR).

Link Lifetime (LLT): Link Expiration Time (LET) is another name for LLT. The expected amount of time that two nearby vehicles will stay connected is represented by this LLT. To assess the sustainability of the link, the LLT is introduced. Equation (13) describes a bigger LLT value, which indicates that the link is more sustainable,

$$LLT_{ij} = \frac{|\Delta v_{ij}| \cdot R - \Delta v_{ij} \cdot \Delta d_{ij}}{(\Delta v_{ij})^2} \quad (13)$$

The LLT is represented by Equation (13). The velocity and distance difference between V_i and V_j are represented by Δv_{ij} and Δd_{ij}. A vehicle's transmission range is represented by R.

3.2.2. CHS using SAMPA

Gathering information from every node is the responsibility of the CH. After then, the sink node received the collected data. The lifetime of WSN is significantly impacted by the choice of CHs. The highest RE, highest LQ, highest CD, lowest Mo, and largest number of neighbour nodes are the characteristics of an ideal CH. For inter-cluster data forwarding, CHs use QoS-aware routing, also known as MO path selection.

The role of vehicles in VANET may change frequently due to their high Mo, which results in additional maintenance costs. When all of its CMs are lost, the CH in the suggested scheme lowers from the CH role and returns to the starting node state. If not, it stays as CH until the cluster merging procedure is completed. As a population-based algorithm, SAMPA works. Equation (14), kind is the periodic distribution of the original CH solution over the search space (clustering) for initial creation,

$$X_0 = X_{min} + rnd(X_{max} - X_{min}) \quad (14)$$

Here, the lower and upper boundaries of the parameters are represented as $X_{min}$and X_{max}.The random vector between 0 and 1 is denoted as rnd. The best CH solution found in the MPA context is recognised as the dominant Predators, and it is essential to the formation of the Elitematrix by Equation (15). By using the positional data of the prey itself, these matrices are useful in tracking and locating prey [25].

$$\text{Elite} = \begin{bmatrix} X^I_{1,1} & X^I_{1,2} & \dots & X^I_{1,d} \\ X^I_{2,1} & X^I_{2,2} & \dots & X^I_{2,d} \\ \vdots & \vdots & \dots & \vdots \\ X^I_{n,1} & X^I_{n,2} & \dots & X^I_{n,d} \end{bmatrix}_{n \times d} \quad (15)$$

The optimum predator vector is indicated by $X_{n,d}$ for the Elite matrix. Here, the number of predators is indicated as n. The count of dimensions for the CH search spaceis denoted by d. When the best predators are replaced by a superior agent, the Elite matrix is updated. The Elite matrix and Prey matrix have comparable dimensionalities. Prey matrix is used by agents pursuing prey to modify their CH positions. The best predators as ideal CH are therefore in charge of establishing the Elite matrix. When creating initial Prey matrix, the CH stage initialisation is essential [25]. The Prey matrix can be expressed using Equation (16),

$$\text{Prey} = \begin{bmatrix} X_{1,1} & X_{1,2} & \dots & X_{1,d} \\ X_{2,1} & X_{2,2} & \dots & X_{2,d} \\ \vdots & \vdots & \dots & \vdots \\ X_{n,1} & X_{n,2} & \dots & X_{n,d} \end{bmatrix}_{n \times d} \quad (16)$$

The optimisation method of the MPA is split into three stages [25],

Stage 1-High Velocity Ratio (HVR): Underscoring the significance of exploration in the CHS, when the predators' speed surpasses that of the prey. Equation (17) provides the mathematical expression of this stage,

$$\text{stepsize}_i = R_B \otimes (\text{Elite}_i - R_B \otimes \text{Prey}_i), i = 1, \dots, n, \text{where} t < T_{max}/3 \quad (17)$$

Using a randomly distributed vector that is regularly distributed, $R_B$is represents the Brownian Motion. By multiplying R_B, The symbol ⊗ represents the entry-wise multiplications that replicate the motion of the prey. A vector of arbitrary values R, spanning from 0 to 1, and a constant number P are introduced in this phase. Equation (18) displays the revised prey position,

$$\text{Prey}_i = \text{Prey}_i + P \cdot R \otimes \text{stepsize}_i \quad (18)$$

Stage 2-Uniform Velocity Ratio (UVR): Predators and prey move at similar speeds during this stage. Exploration and exploitation must be balanced throughout this stage. Exploration is assigned to half of the agents, while exploitation is assigned to the other half. Predators and prey split these CHS tasks. In this stage, the following is the mathematical representation [25],

$$\text{stepsize}_i = R_L \otimes (\text{Elite}_i - R_L \otimes \text{Prey}_i), i = 1, \dots, \frac{n}{2}, \text{where} \frac{T_{max}}{3} < t < \frac{2T_{max}}{3} \quad (19)$$

Equation (20) represents the revised prey location,

$$\mathrm{Prey_i} = \mathrm{Prey_i} + \mathrm{P} \cdot \mathrm{R} \otimes \mathrm{stepsize_i} \quad (20)$$

Levy Flight (LF) is the basis for the randomly generated vector known as RL. By adding the place of the prey to the CHS step size, it replicates the movement of the prey. According to the MPA, Equations (21)-(23) dictate that the remaining half of the population followed by the regulations [26],

$$\mathrm{stepsize_i} = \mathrm{R_B} \otimes (\mathrm{R_B} \otimes \mathrm{Elite_i} - \mathrm{Prey_i}), \mathrm{i} = \frac{\mathrm{n}}{2}, \dots, \mathrm{n} \quad (21)$$

$$\mathrm{Prey_i} = \mathrm{Elite_i} + \mathrm{P} \cdot \mathrm{CF} \otimes \mathrm{stepsize_i} \quad (22)$$

$$\mathrm{CF} = \left(1 - \frac{\mathrm{t}}{\mathrm{T_{max}}}\right)^{2 \times \frac{\mathrm{t}}{\mathrm{T_{max}}}} \quad (23)$$

Stage 3-Low Velocity Ratio (LVR): This stage occurs when the prey (CH) proceeds more slowly than the predators [25],

$$\mathrm{stepsize_i} = \mathrm{R_L} \otimes (\mathrm{R_L} \otimes \mathrm{Elite_i} - \mathrm{Prey_i}), \mathrm{i} = 1, \dots, \mathrm{n}, \text{ where} \mathrm{t} > \frac{2\mathrm{T_{max}}}{3} \quad (24)$$

$$\mathrm{Prey_i} = \mathrm{Elite_i} + \mathrm{P} \cdot \mathrm{CF} \otimes \mathrm{stepsize_i} \quad (25)$$

$$\mathrm{CF} = \left(1 - \frac{\mathrm{t}}{\mathrm{T_{max}}}\right)^{2 \times \frac{\mathrm{t}}{\mathrm{T_{max}}}} \quad (26)$$

The behaviour of algorithms can be affected by Fish Aggregation Devices (FADs). These elements impact the optimisation process and serve as local optima avoidance operators. In order to reduce stagnation in LO, longer hops are taken during simulation. Equation (27), which describes the impact of FADs,

$$\mathrm{Prey_i} = \begin{cases} \mathrm{Prey_i} + \mathrm{CF}[(\mathrm{X_{max}} - \mathrm{X_{min}}) \otimes \mathrm{R} + \mathrm{X_{min}}] \otimes \mathrm{U}, \mathrm{if} \, \mathrm{r} \leq \mathrm{FADs} \\ \mathrm{Prey_i} + (\mathrm{Prey_1} - \mathrm{Prey_2})[\mathrm{FADs}(1 - \mathrm{r}) + \mathrm{r}], \mathrm{if} \, \mathrm{r} > \mathrm{FADs} \end{cases} \quad (27)$$

MPA dynamics are defined by these stages and flexible approaches. A new optimisation technique that incorporates an adaptable weight parameter is presented. When an optimal CH is selected by a fitness function, the suggested method maintains good performance in LO while enhancing the global search capability and escaping from LO by utilising this parameter. In particular, the suggested method speeds up the global search of the solution space in the early phases of optimisation [25]. Create a self-adaptive weight position-update system to take advantage of the destination point's positioning information,

$$\mathrm{Prey_i} = \omega \cdot \mathrm{Prey_i} + \mathrm{P} \cdot \mathrm{R} \otimes \mathrm{stepsize_i}, \mathrm{i} = 1, \dots, \mathrm{n}, \text{where} \mathrm{t} < \mathrm{T_{max}}/3 \quad (28)$$

$$\mathrm{Prey_i} = \begin{cases} \omega \cdot \mathrm{Prey_i} + \mathrm{P} \cdot \mathrm{R} \otimes \mathrm{stepsize_i}, \mathrm{i} = 1, \dots, \mathrm{n}/2 \\ \omega \cdot \mathrm{Elite_i} + \mathrm{P} \cdot \mathrm{CF} \otimes \mathrm{stepsize_i}, \mathrm{i} = \mathrm{n}/2, \dots, \mathrm{n} \end{cases} \text{where} \frac{\mathrm{T_{max}}}{3} < \mathrm{t} < 2\mathrm{T_{max}}/3 \quad (29)$$

$$\mathrm{Prey_i} = \omega \cdot \mathrm{Elite_i} + \mathrm{P} \cdot \mathrm{CF} \otimes \mathrm{stepsize_i}, \mathrm{i} = 1, \dots, \mathrm{n} \quad (30)$$

$$\omega = (\omega_{\mathrm{int}} - \omega_{\mathrm{end}}) \times \mathrm{R} \times \frac{(\mathrm{n}-\mathrm{i})\mathrm{Prey_i}}{\mathrm{nElite_i}}, \omega_{\mathrm{int}} = 0.9, \omega_{\mathrm{end}} = 0.4, \text{where } \mathrm{t} > 2\mathrm{T_{max}}/3 \quad (31)$$

By adjusting the weight parameters according to the objective function in Equation (1), the function of the suggested model is minimised in this study. In this study, dynamic correction is guided by a self-adaptive weight ω in the update formula. Here, the global optimal fitness value is indicated by $\mathrm{Elite_i}$. The $\mathrm{Prey_i}$ variable indicates the location variable's optimal fitness value for the existing iteration. The weight between the present CH position and the destination point is dynamically adjusted by it. Global search capabilities are improved, and the search space for practical CH solutions is expanded when once the current CH position variable's fitness value exceeds the global fitness value, the inertia weight increases. However, a reduced value is produced by the self-adaptive weight, which facilitates local refining and encourages higher rates of convergence. To decrease the probability of entering local optima and increase accuracy, particles in the MPA can independently choose between global and local phases in the self-adaptive weight.

Algorithm 1. Self-Adaptive Marine Predators Algorithm (SAMPA)

1. Set populations, iteration t=1
2. While ($\mathrm{t} \leq \mathrm{T_{max}}$) do
3. For optimal CHS, compute the fitness and construct the Elite matrix.
4. Update self-adaptive weight ω by Equation (13)
5. if $\mathrm{t} < \mathrm{T_{max}}/3$ then
6. Update the prey location for optimal CHS using Equation (28)
7. else if $\mathrm{T_{max}}/3 < \mathrm{t} < 2\mathrm{T_{max}}/3$ then
8. Use Equation (29) to update the prey location for the first portion of the population
   //$\mathrm{i} = 1, \dots, \mathrm{n}/2$

9. Update the prey's location for the other half by Equation (29) //$i = n/2, \ldots, n$
10. else if $t > 2T_{max}/3$ then
11. Update prey location by Equation (30)
12. end if
13. Apply the FAD effect by Equation (27)
14. Ensure the use of the Elite and memory-saving updates.
15. t=t+1
16. end while
17. return the best location ($Elite_i$)

3.2.3. Cluster Formation

The vehicle enters a cluster and is in the IN state if it receives beacons or ACK signals from a CH. The vehicle initiates a join response timer (JOIN_TIMER) after sending a JOIN_REQ message to the relevant CH after first transferring its status to CCM. The vehicle switches from CCM to CM after receiving the JOIN_RESP message. Vehicles reset their state to IN if they don't receive any response messages. Thus, in the IN state, messages from many CH are received by a vehicle. V_i. Since CH_j has the longest Link Lifespan (LLT_{ij}), the vehicle selects it in this case.

The CH initially determines the total number of members in the CM_LIST after receiving a JOIN_REQ message from the environment. If the number of CMs is less than the maximum number of members allowed (MAX_CM), the CH transmits a JOIN_RESP message to the vehicle after receiving a JOIN_REQ message.

The CH creates a vehicle entry and adds it to the CM_LIST in the meantime. The CM will be in charge of forwarding the packet to vehicles in adjacent clusters if it originates from its CH. In order to locate a neighbour CH that is approaching the target intersection, the CM first looks through the neighbour list. The CM chooses the CH that is closest to the target intersection if there are many CHs. The chosen CH will then receive the DATA_PACKET. As the next propagation vehicle, the CM will select the one-hop neighbour closest to the subsequent intersection if it is unable to locate a CH in the neighbour list.

3.2.4. Cluster Maintenance

The role of vehicles in VANET may change frequently due to their great mobility, the maintenance costs are also increased. In the suggested plan, upon losing all of its CMs, the CH leaves the CH position and moves to the IN state. Until the cluster merging operation is completed, it stays as CH otherwise. Beacon messages are used by vehicles to communicate with each other. The vehicle's identification, present location, recent speed, moving way, vehicle's current condition, and CH's identity, if it is a CM, are all included in the beacon message. This beacon message is broadcast and gathered at each beacon interval.

3.3. Aquila Optimizer-Based Multi-Objective Routing (AOMOR) Strategy

AOMOR optimisation algorithm simulates the hunting behaviour of aquilas for the best route selection from source to destination [26].

Initialisation, exploration, exploitation, and eventually arriving at the best solution are its four primary phases. During the optimal CHS, the MO, such as MRL, PDR, throughput, E2ED, and CPO [27, 28]. Equation (32) provides the multi-objective function,

$$obj = \alpha_1 * F_1 + \alpha_2 * (1 - F_2) + \alpha_3 * (1 - F_3) + \alpha_4 * F_4 + \alpha_5 * F_5 \tag{32}$$

Where the fitness functions for MRL, PDR, throughput, E2E Delay, and CPO are indicated by F_1, F_2, F_3, F_4, and F_5,α_1, α_2, α_3, α_4, $\alpha_5$are the weights. Equation (33) is denoted as the Fuzzy Membership Function (FMF) to calculate these weights,

$$\alpha = \begin{cases} 0 & \text{if} UB < f \\ \frac{UB-f}{LB-f} & \text{if} f \le UB \le LB \\ \frac{MB-UB}{MB-LB} & \text{if} LB \le UB \le MB \\ 0 & \text{if} UB \ge LB \end{cases} \tag{33}$$

Where the triangular membership function T(f) vertices are shown by LB, MB, and UB, the LB is indicated by a value of 1, the MB by a value of 1, and the UB by a value of 0.

MRL (F1): The rate of the count of packets sent, including those that are forwarded, is known as MRL. Equation (34) provides a mathematical representation of the MRL,

$$F_1 = \frac{P_{send}}{P_{received}} \tag{34}$$

Where $P_{send}$is denoted as the count of sent packets,$P_{received}$ is the count of received packets.

PDR (F2): Equation (35) can be used to get F2. The ratio of the number of packets delivered from the source to the number of packets received at the destination,

$$F_2 = \frac{P_{received}}{P_{generated}} \tag{35}$$

Where the number of created packets is indicated by $P_{generated}$.

Throughput (F3): In a communication network, the average speed at which a data packet efficiently travels among two nodes,

$$F_3 = \frac{P_{received} * P_{size}}{T} \quad (36)$$

Where the packet size is indicated by P_{size}. The entire time is indicated by Throughput.

E2ED (F_4): For every network link, it is the sum of the various kinds of delays.

$$F_4 = N * [D^{trans} + D^{prop} + D^{proc} + D^{que}] \quad (37)$$

Where the transmission delays are denoted asD^{trans}, propagation is denoted as D^{prop}, processing is denoted asD^{proc} and queuing is denoted asD^{que}. Furthermore, the number of network links is represented by N.

CPO (F_5): The percentage of controlling data bytes used by the transmitter to create a secure connection between the transmitter and the receiver to the CPO is the total of all application data bytes exchanged between the sender and the recipient,

$$F_5 = \frac{(\sum_{i=1}^{M} RRQ_i + \sum_{i=1}^{M} RRT_i) * S_{request}}{\sum_{i=1}^{M}(P_{send} * S_A) + (\sum_{i=1}^{M} RRQ_i + \sum_{i=1}^{M} RRT_i) * S_{request}} \quad (38)$$

Where the number of RRQ produced by the sender is indicated by RRQ_i. RRT_i indicates how many times the sender has tried to send the route request. The dimension of the request packet (in bytes) is denoted as $S_{request}$. The dimension of the application DP corresponding to application i is denoted as S_A.Population X is initialised as the number of routes with N agents at the beginning of the initialisation step,

$$X_{ij} = r_1 \times (UB_j - LB_j) + LB_j, i = 1, \ldots, N, j = 1, \ldots, Dim \quad (39)$$

Where the route selection search space's upper and lower bounds are indicated by$UB_j$and LB_j. The count of problem dimensions is denoted as Dim, and the random value is $r_1 \in [0, 1]$. Exploration or exploitation is the next steps in the AO method until the optimal path is found. There are two approaches to both exploration and exploitation [28]. The best agent (X_b) and the average of all agents (X_M)are introduced in the initial strategy to carry out the exploration,

$$X_i(t + 1) = X_b(t) \times \left(\frac{1-t}{T}\right) + (X_M(t) - X_b(t) * rand) \quad (40)$$

$$X_M(t) = \frac{1}{N} \sum_{i=1}^{N} X(t), \forall j = 1, \ldots, Dim \quad (41)$$

The maximum iteration count is denoted as T. To enhance the path solution capability for exploration, the second technique, X_b the Levy flight Levy (D) distribution,

$$X_i(t + 1) = Levy(D) \times X_b(t) + X_R(t) + (y - x) * rand \quad (42)$$

$$Levy(D) = s \times \frac{u \times \sigma}{|v|^{1/\beta}}, \sigma = \left(\frac{sine\left(\frac{\pi\beta}{2}\right) \times \Gamma(1+\beta)}{\beta \times 2^{\left(\frac{\beta-1}{2}\right)} \times \Gamma\left(\frac{1+\beta}{2}\right)}\right) \quad (43)$$

Where u and v are arbitrary integers, the constants s = 0.01 and β = 1.5. Equation (42) X_R is a randomly selected agent. Additionally, the spiral shape is mimicked using y and x in the following way,

$$y = r \times \cos(\theta), x = \sin(\theta) \times r \quad (44)$$

$$r = r_1 + U \times D_1, \theta = -\omega \times D_1 + \theta_1, \theta_1 = \frac{3 \times \pi}{2} \quad (45)$$

Where $r_1 \in [0, 20]$ is a random number and w = 0.0050 and U = 0.005650 are arbitrary values. The initial approach, which is based on $X_b$and X_M, is calculated during the exploitation phase [28],

$$X_i(t + 1) = (X_b(t) - X_M(t)) \times \alpha - rand + ((UB - LB) \times rand + LB) \times \delta \quad (46)$$

Where α and δ provide the parameters for exploitation adjustment. The value rand [0, 1] is a random value. In the second exploitation phase, Levy $X_b$and the quality function QF,

$$X_i(t + 1) = QF \times X_b(t) - (G_1 \times X(t) \times rand) - G_2 \times Levy(D) + rand \times G_1 \quad (47)$$

$$QF(t) = t^{\frac{2 \times rand() - 1}{(1-T)^2}} \quad (48)$$

Furthermore, a number of motions are denoted as G_1 Equation (49) uses to monitor the ideal solution,

$$G_1 = 2 \times rand() - 1 \quad (49)$$

The rand represents a random value, G_2 is decreased from 2 and 0,

$$G_2 = 2 \times \left(1 - \frac{t}{T}\right) \quad (50)$$

Data transmission with the lowest transfer latency and the maximum connectivity stability is the goal of the AOMOR protocol.

4. Results and Discussion

This proposed approach is compared with three previously clustering-based schemes, like RAMO [18], HFCHBO [20], SHR-ACO [22], and HHPOASCCP [24]. With SUMO-generated vehicle mobility, the simulations are run in the Network Simulator NS-2 (v-2.35). A typical urban setting measuring 5000 m × 5000 m serves as the simulation scenario. To allow all of the injected vehicles to roam over the map for a time, run the simulation for 100 seconds after setting the number of simulated vehicles to 1500. To assess overall performance indicators, the simulation continues for an additional 500 s after the first 100. Analyse the metrics in the simulation at the 200 and 500 m transmission ranges. In the meanwhile, set the maximum acceleration and deceleration at 5 m2/s and change the maximum permitted vehicle velocity from 10 to 30 m/s. The average of ten runs is the result that is reported. Table 1 contains a detailed list of simulation parameters and values.

Table 1. Simulation parameters

Parameter	Description
Simulation range	2000 m×2000 m
Mobility model	SUMO routes
Propagation model	Two-Ray / Nakagami-m
High velocity	10,15,20,25, and 30 m/s
High Acceleration	5 m/s^2
Transmission Range	200 m, 500 m
Transmission Energy	23 dBm
Data Rate	6 Mbps
MAX_CM	10
HELLO_PACKET PERIOD	200 ms
HELLO_PACKET Dimension	64 bytes
DATA_PACKET Generation Rate	10,20,30, 40, 50 packet/seconds
DATA_PACKET dimension	1024 bytes
IN_TIMER	1s
CH_TIMER	2s
JOIN_TIMER	2s
CHS period	2s
Maximum cluster dimension	20 nodes
CH hold time	10 s
Speed(m/s)	10-20
Traffic	CBR/ Poisson model
Beacon Rate	5-10 Hz
Beacon TTL/Hop	1 hop
Beaconing for cluster	2 Hz
Maximum Hops (Data)	6
MAC Protocol	IEEE 802.11 p
Channel	5.9 GHz
Queue Length	100 packets
CH election period	2s
Maximum cluster dimension	20 nodes
CH hold time	10 s
Weight factors	$w_2 = 0.3, w_5 = 0.25, w_3 = 0.2, w_4 = 0.15, w_1 = 0.1$

4.1. Performance Evaluation Metrics

PDR, PLR, E2ED, throughput, and ARE were employed for evaluating the efficiency of the proposed model and existing methods.

PDR: In Equation (51), proportion of forwarded packets that arrive at their destination successfully is measured by PDR,

$$\text{PDR} = \frac{\text{No.of packets Received}}{\text{Total no.of packets sent}} * 100 \tag{51}$$

PLR: In Equation (52), the percentage of forwarded packets that do not reach their destination is measured by PLR,

$$\text{PLR} = \frac{\text{No.of packets Lost}}{\text{Total no.of packets sent}} * 100 \tag{52}$$

PDR and PLR are inversely proportional: a higher PDR means a lower PLR, indicating better network reliability and performance.

E2ED: In Equation (53), the entire amount of time a packet spends travelling across a network, including processing, waiting, and transmission times at each hop, is known as E2ED,

$$D_{E2E}(i,j) = \sum_{k=1}^{H}\left(D_{trans}^{(k)} + D_{prop}^{(k)} + D_{proc}^{(k)} + D_{queue}^{(k)}\right) \quad (53)$$

where the hop countamong source i and destination j is denoted by H.$D_{trans}^{(k)}$ is denoted as the transmission delay at node k. The propagation delay at node k is represented by $D_{prop}^{(k)}$. The processing delay at node k is represented by $D_{proc}^{(k)}$.$D_{queue}^{(k)}$ is denoted as the queuing/waiting delay at node k. Throughput: In Equation (54), the quantity of data that may be effectively sent over a network in a given period of time is known as throughput,

$$\text{Throughput} = \frac{\text{Total Data Received(bits)}}{\text{Total simulation time(Seconds)}} * 100 \quad (54)$$

Residual Energy (RE): RE is the remaining energy of nodes after simulation or after several communication rounds. RE is calculated by Equation (55),

$$RE = En_{Int} - En_{Con} \quad (55)$$

Where the initial energy is indicated by En_{Int}.En_{Con} is denoted as the energy spent on transmission, reception, idle, and processing. ARE is calculated by Equation (56),

$$ARE = \frac{\sum_{j=1}^{M} RE_j}{M} \quad (56)$$

Where M is denoted as the total number of nodes.

4.2. Results Comparison of QoS Metrics

The efficiency of the suggested framework and current approaches are evaluated using key metrics, including PDR, PLR, E2E delay, throughput, and ARE. It has been clearly discussed in Table 2. The proposed system has increased PDR, reduced PLR, reduced E2E delay, increased throughput, and increased ARE of 92.16%, 7.84%, 183.54 ms, 44.41 Kbps, and 74.08 J.

Table 2. QoS Metrics comparison of routing protocols

Number of rounds/ Methods	**PDR (%)**					
	400	**800**	**1200**	**1600**	**2000**	**Average**
RAMO	86.09	84.16	82.08	81.35	80.27	82.79
SHR-ACO	87.82	86.65	85.43	83.27	81.75	84.98
HFCHBO	89.37	88.74	87.41	85.65	84.57	87.15
HHPOASCCP	91.66	90.45	89.61	87.33	86.26	89.06
AOMOR	94.54	93.61	92.47	90.65	89.52	92.16
Number of rounds/ Methods	PLR (%)					
	400	800	1200	1600	2000	Average
RAMO	13.91	15.84	17.92	18.65	19.73	17.21
SHR-ACO	12.18	13.35	14.57	16.73	18.25	15.02
HFCHBO	10.63	11.26	12.59	14.35	15.43	12.85
HHPOASCCP	8.34	9.55	10.39	12.67	13.74	10.93
AOMOR	5.46	6.39	7.53	9.35	10.48	7.84
Number of rounds/ Methods	E2E Delay (ms)					
	400	800	1200	1600	2000	Average
RAMO	267.16	254.83	242.6s9	227.75	215.79	241.65
SHR-ACO	246.92	237.26	226.58	215.68	207.37	226.76
HFCHBO	232.71	221.81	215.06	203.57	193.64	213.35
HHPOASCCP	220.85	207.57	198.51	187.44	175.72	198.02
AOMOR	205.87	190.45	182.76	175.14	163.49	183.54
Number of rounds/ Methods	Throughput (Kbps)					
	400	800	1200	1600	2000	Average
RAMO	21.72	25.66	29.17	34.35	39.25	30.03
SHR-ACO	24.45	28.81	32.53	37.46	43.67	33.38
HFCHBO	27.86	31.38	35.65	41.37	46.52	36.56
HHPOASCCP	30.92	34.59	38.78	44.64	50.78	39.94
AOMOR	33.65	37.73	43.86	49.82	56.97	44.41
Number of rounds/ Methods	Average Residual Energy (ARE) (j)					
	400	800	1200	1600	2000	Average

RAMO	78.25	73.37	62.54	49.67	38.85	60.54
SHR-ACO	82.19	76.42	65.57	54.79	42.81	64.36
HFCHBO	84.68	78.94	67.61	57.82	45.29	66.87
HHPOASCCP	86.21	80.65	71.38	62.91	48.38	69.91
AOMOR	88.63	83.77	75.19	66.85	55.96	74.08

4.2.1. Analysis of PDR Comparison

One important statistic is PDR. The rate of packets that are effectively delivered to the destination relative to the total $P_{generated}$ The source is known as the PDR. Minimal data loss and transmission is indicated by a higher PDR. Figure 3 displays the findings from the different PDR analysis routing protocols. The suggested design has superior PDR performance compared to the other approaches.

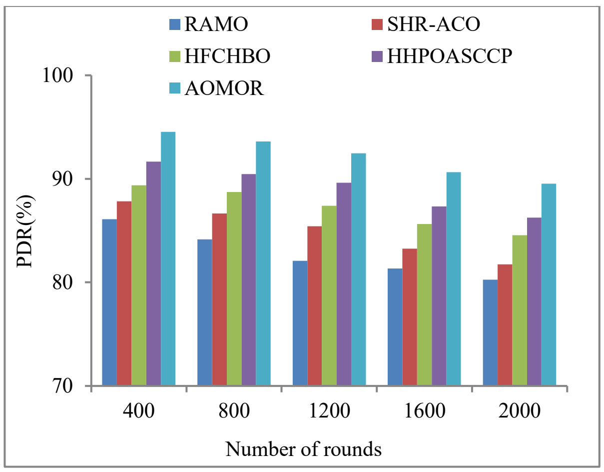

Fig. 5 PDR comparison of routing protocols

The PDR comparison of routing protocols with relation to the number of rounds ranging from 400 to 2000 is shown in Figure 5. As the number of rounds increases, the proposed system consistently achieves the highest PDR, reaching 89.52%, whereas other methods, such as RAMO (80.27%), SHR-ACO (81.75%), HFCHBO (84.57%), and HHPOASCCP (86.26%), demonstrate lower PDR values.

Furthermore, the proposed system also achieves the highest average PDR of 92.16%, while the average PDR values of RAMO, SHR-ACO, HFCHBO, and HHPOASCCP are 82.79%, 84.98%, 87.15%, and 89.06%, respectively. This clearly indicates the superior packet delivery performance of the suggested method over current routing protocols.

The proposed AOMOR obtains the maximum PDR throughout all simulation rounds, due to its reliable Cluster Head selection using SAMPA and QoS-aware multi-objective routing method. In addition, the Digital Twin-based network monitoring allows proactive route adaptation, achieving less packet loss and better communication dependability compared to conventional approaches.

4.2.2. Analysis of PLR Comparison

The PLR is the percentage of packets which are not successfully delivered to destination relative to the total number of $P_{generated}$ from the source. The PLR with the lowest value indicates the least information loss throughout transmission. Figure 4 displays the findings from the PLR.

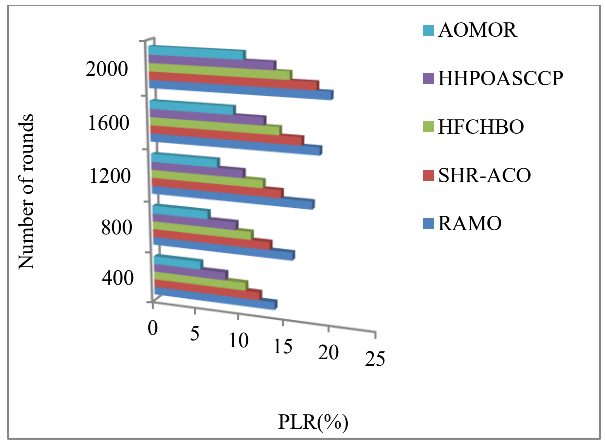

Fig. 6 PLR comparison of routing protocols

The PLR comparison with relation to the number of rounds, which ranges from 400 to 2000, is shown in Figure 6. The suggested system continuously attains the lowest PLR of 10.48% as the number of rounds rises. The other methods, such as RAMO (19.73%), SHR-ACO (18.25%), HFCHBO (15.43%), and HHPOASCCP (13.74%), exhibit higher PLR values. The proposed method shows the lowest average PLR of 7.84%, while the average PLR values of RAMO, SHR-ACO, HFCHBO, and HHPOASCCP are 17.21%, 15.05%, 12.85%, and 10.93%, respectively. These results clearly demonstrate that the suggested method overtakes the current routing protocols by effectively reducing packet loss across increasing rounds. Due to its stable SAMPA-based cluster formation and QoS-aware route selection, the proposed AOMOR minimizes packet drops and route failures, resulting in the least PLR in all the simulated rounds. In addition, Digital Twin-enabled monitoring enables proactive congestion and link management, which leads to dramatically reduced packet loss compared to conventional approaches.

4.2.3. Analysis of E2E Delay Comparison

Reducing delay is a crucial problem in the data routing process when it comes to ensuring vehicle safety. To improve safety and lower the chance of collisions, it is essential that the pertinent data from routing gets into the appropriate nodes as soon as possible. In order to prevent collisions, this low-latency data transmission is essential.

Figure 7 illustrates the comparisons of E2ED with respect to the number of rounds ranging from 400 to 2000. As the count of rounds increases, the suggested method reliably attains the lowest E2E delay of 163.49 ms, while other methods, such as RAMO (215.79 ms), SHR-ACO (207.37 ms), HFCHBO (193.64 ms), and HHPOASCCP (175.72 ms), exhibit comparatively higher delays. With respect to the average performance, the proposed system gives the lowest average E2E delay of 183.54 ms, whereas the average delays of RAMO, SHR-ACO, HFCHBO, and HHPOASCCP are 241.65 ms, 226.76 ms, 213.35 ms, and 198.02 ms, respectively.

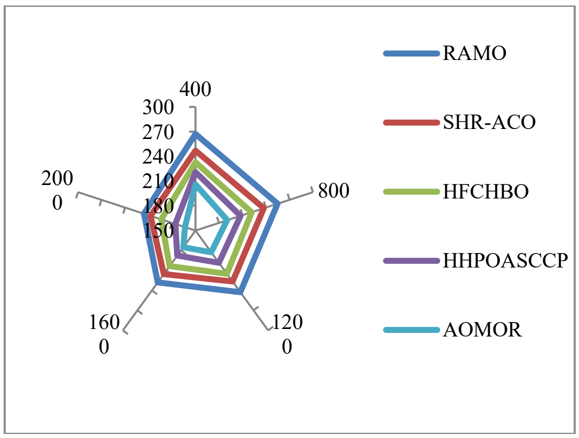

Fig. 7 E2ED comparison of routing protocols

These findings clearly indicate that the suggested method, when compared to the current routing protocols, ensures faster data delivery across increasing rounds. The proposed AOMOR achieves the lowest End-to-End Delay (E2E) as it picks stable Cluster Heads by SAMPA and discovers optimal routing paths with minimum transmission and routing overhead by AOMOR.

Moreover, Digital Twin-assisted monitoring allows for rapid route adaptation to network changes, leading to a substantial latency reduction over current methods.

4.2.4. Analysis of Throughput Comparison

In a VANET, throughput is the number of packets processed per second. By altering the number of rounds, the value of the throughput analysis for a VANET has been determined. Figure 6 displays the obtained results. The predicted model has demonstrated greater throughput for each variation in the round of rounds after analysing the obtained results.

The routing protocols' throughput comparison is shown in Figure 8 in relation to the number of rounds, which ranges from 400 to 2000.

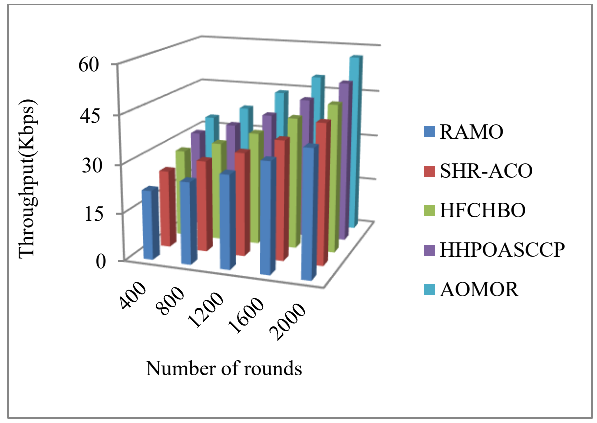

Fig 8. Throughput comparison of routing protocols

As the number of rounds increases, the proposed system consistently achieves the increased throughput of 56.97 Kbps, while other methods, such as RAMO (39.25 Kbps), SHR-ACO (43.67 Kbps), HFCHBO (46.52 Kbps), and HHPOASCCP (50.78 Kbps), exhibit the lowest throughput. In the context of the average performance, the proposed system gives the highest throughput of 44.41 Kbps, whereas the average throughput of RAMO, SHR-ACO, HFCHBO, and HHPOASCCP are 30.03 Kbps, 33.38 Kbps, 36.56 Kbps, and 39.94 Kbps, respectively. The proposed AOMOR selects stable Cluster Heads and appropriate communication pathways to obtain the best throughput in all simulation rounds. This, in turn, minimizes packet retransmissions and routing disturbances. Moreover, Digital Twin-assisted traffic monitoring improves the network resource usage and link stability, resulting in far higher data delivery rates than the current approaches.

4.2.5. Analysis of ARE Comparison.

One important metric that provides information about the network's lifespan is the energy consumption of nodes during data transmission. Some nodes can function for longer periods of time due to lower energy consumption, which makes data routing more efficient.

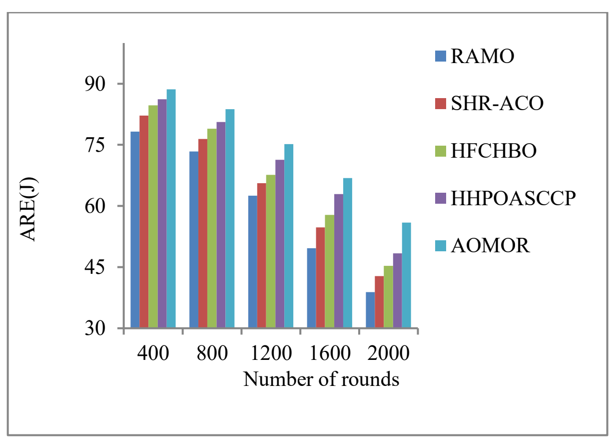

Fig 9. ARE comparison of routing protocols

Routing protocols with respect to the count of rounds ranging from 400 to 2000 of ARE comparison is illustrated in Figure 9. As the count of rounds rises, the proposed system consistently achieves the increased ARE of 55.96 J, while other methods such as RAMO (38.85 J), SHR-ACO (42.81 J), HFCHBO (45.29 J), and HHPOASCCP (48.38 J) exhibit lowest ARE. In terms of the average performance, the proposed system gives the highest ARE of 74.08 J, whereas the average ARE of RAMO, SHR-ACO, HFCHBO, and HHPOASCCP are 60.54 J, 64.36 J, 66.87 J, and 69.91 J, respectively. The proposed an AOMOR has the highest Average Residual Energy (ARE) for the whole simulation, as SAMPA selects energy-efficient Cluster Heads and reduces the needless communication overhead. Furthermore, it improves energy preservation compared to previous approaches using efficient routing and Digital Twin-assisted network management to reduce energy usage.

5. Conclusion and Future Work

In this paper, a novel QoS-driven routing mechanism is developed by merging Aquila Optimizer (AO) for routing and the Self-Adaptive Marine Predators Algorithm (SAMPA) for CHS. Clustering serves as an efficient technique to manage the dynamic and high-mobility characteristics of vehicular networks by dividing them into virtual groups known as clusters, each governed by a CH. Data from CM must be aggregated by the CH before being sent to the sink node. SAMPA is introduced to choose the best CH several fitness factors, such as a greater number of neighbouring nodes, maximal ND, higher RE, stronger LQ, higher CD, and minimal mobility. Dominating predator, the algorithm imitates the foraging tactics of marine predators, such as HVR, UVR, and LVR. Furthermore, SAMPA is enhanced by the introduction of an adaptive weight factor to achieve more reliable CH selection under varying network conditions. AO is employed for route optimization within the VANET. AO utilizes different searching, swooping, and attacking strategies and identifies optimal routing paths by the hunting behavior of eagle species. By combining SAMPA-based CH selection with AO-based routing, the suggested scheme ensures QoS-aware communication with improved reliability, reduced latency, and enhanced energy efficiency. Informed decisions about routing protocol are made by the suggested model, which uses digital twin technology to analyse network behaviour and forecast traffic trends. To reduce congestion and meet the security needs of real-time VANET applications, the routing protocols will be further improved in further work.

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