Enhancing Urban VANETs with Density-Based Hexagonal Clustering and Whale Optimization

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Abstract: In recent years, Vehicular Ad-hoc Networks (VANETs) have emerged as a key area of interest for advancing Intelligent Transport Systems. This paper introduces an innovative approach called Efficient Clustering Routing with a novel clustering algorithm based on Spatial Density-Based Clustering (SDC) and Whale Optimization Algorithm (WOA). The methodology begins by leveraging WOA to identify cluster heads, enhancing the selection process through a refined fitness function derived from SDC principles. Clustering is then executed based on the reliability of links among vehicles, optimizing network connectivity. To evaluate the efficacy of the proposed scheme, simulations are conducted using MATLAB, simulating real-world urban scenarios. Specifically, the scheme achieves a 74% reduction in network topology change rate, indicating enhanced stability. Moreover, intra-cluster throughput sees a notable 34% increase, and inter-cluster throughput improves by 47%, showcasing enhanced overall performance. Additionally, there is a 16% decrease in average delay, further validating the effectiveness of the approach in optimizing VANET performance in dynamic urban environments.

Keywords: Clustering, Optimisation, MATLAB, Performance.

1. Introduction

In recent years, there has been a growing interest in Vehicular Ad-hoc Networks (VANETs) among researchers and engineers worldwide. This interest stems from VANET's potential to address traffic and safety challenges and enhance entertainment features within ITS. The surge in vehicle numbers and the unpredictable mobility patterns in urban settings have introduced challenges related to availability, scalability, and overall network stability [1]. These issues notably impact the effectiveness of services like routing. Clustering has emerged as a promising technique, as indicated by several studies, to mitigate these challenges and enhance VANET's reliability and scalability in urban environments [2]. Clustering involves grouping vehicles into clusters, facilitated by Cluster Heads and Cluster Members, enabling better utilization of resources, and providing more secure & reliable routing [3]. This paper presents a novel routing approach leveraging a new clustering method on the Whale Optimization Algorithm (WOA) and Spatial Density-Based Clustering (SDC) algorithm. Initially, WOA is employed to identify cluster heads, with a revised fitness function derived from SDC principles. Subsequently, clustering occurs based on link reliability parameters among vehicles.

The key contributions of this paper include:

- Introducing a novel clustering approach combining WOA and SDC to enhance cluster stability in urban environments.
- Utilizing WOA for cluster head selection, leveraging its universal hunt competence to find optimal solutions and reconstructing the fitness function with distance & density parameters (j and i) based on parameter dc.
- Introducing a criterion factor T to calculate the cut-off parameter d_c in the algorithm, considering node positions, speeds, and directions.
- Classifying vehicles based on link reliability (REL) rather than distance, addressing high-density and mobility challenges.
- Proposing a maintenance phase for re-selecting CHs and clustering vehicles efficiently.

The paper is organized as: Section 2 presents a literature review, Section 3 particulars the theoretical background, Section 4 outlines the main approach steps, Section 5 evaluates effectiveness and compares with NMDP-APC & GAPC Section 6 concludes the paper.

2. OVERVIEW OF RELATED RESEARCH

Numerous studies have explored the impact of urban density on routing within VANETs, with clustering techniques being a central focus. These studies employ a range of approaches, from intelligent routing methodologies to specific clustering algorithms

2.1 Intelligent Routing Strategies

Recent advancements in intelligent techniques, such as Machine Learning (ML), Artificial Intelligence, Deep Learning, and Fuzzy Logic, have been proposed to design sophisticated routing systems [4,5]. These methods address various challenges in ad hoc networks, including packet delivery rates, end-to-end delay, energy consumption, route stability, and routing overhead [6]. A comprehensive survey discusses the benefits and applications of these techniques in VANET environments. Previous works have applied diverse intelligent methods to enhance clustering in VANETs, including Global Affinity Propagation Clustering, Particle Swarm Optimization (PSO), Bio-inspired metaheuristic frameworks, and Grasshopper Optimization [7,8,9,10]. While these approaches target reduced communication latency, they often require substantial computational resources and memory [11]. For example, [12] introduced a clustering algorithm based on Grasshopper Optimization for VANETs to reduce network overhead in dense scenarios, but did not evaluate its performance in terms of clustering efficiency or isolated vehicles. Similarly, [13] proposed a PSO-based cluster routing scheme for V2V communication to improve transmission link stability, yet it did not address the role of density in clustering effectiveness [14].

2.2 Hexagonal Clustering Approach

Recent research has introduced various clustering algorithms designed for urban VANET environments, focusing on factors like position, velocity, and direction. For instance, a novel clustering algorithm that combines spectral clustering and force-directed algorithms aims to optimize cluster lifetimes and VANET stability. However, the effectiveness of this approach concerning other routing parameters remains unexplored [15]. The Unified Framework of Clustering (UFC) [16] enhances cluster performance by improving formation efficiency and stability but requires high computational resources and memory. Other approaches, such as a stable and scalable clustering algorithm based on center-based grid partitioning, leverage V2I communication and global views but may benefit from more realistic simulation results using tools like SUMO [17]. Lastly, [18] proposed a stable clustering algorithm incorporating bus traffic regularity and vehicle mobility parameters, yet it does not integrate vehicle density—a critical urban parameter—into its approach.

Our proposed method addresses these gaps by (i) incorporating vehicle density in clustering, (ii) determining density criteria based on a specified criterion T, (iii) using the Whale Optimization Algorithm (WOA) for Cluster Head (CH) selection due to its global search capability, and (iv) integrating link reliability modelling to optimize vehicle distribution within clusters [19]. We will provide specific data and examples to support these contributions and demonstrate how our method overcomes limitations present in prior approaches.

2. Theoretical foundation

In this section, we delve into the theoretical underpinnings of our proposed solution, starting with an overview of the Whale Optimization Algorithm and its structure, followed by a discussion on the Density Peaks Clustering algorithm's key aspects and strengths.

3.1 Whale Optimization Algorithm (WOA)

WOA fits in to the class of swarm intelligence approaches and is repeatedly applied to optimization glitches. Inspired by bird flocking behavior, WOA operates as a population-based search algorithm. Each particle, representing an individual in the search space, navigates with flexible speed. Particle velocity and position dynamically modification within the swarm, influenced by personal flight experiences and social-psychological tendencies. By leveraging memory, particles remember optimal positions, aiding in search space navigation and solution convergence.

WOA offers several advantages:

- Simple understanding and implementation.
- Few adjustable parameters.
- Minimal computational overhead.
- Velocity-based optimization for efficient convergence.

These characteristics make WOA a promising choice for CH selection in clustering algorithms for VANETs.

Definitions and Variables:

- Population Size (N): Number of whales in the population.
- Maximum Iterations (MaxIter): Maximum number of iterations before termination.
- Convergence Criteria (ε): Threshold for determining convergence.
- Position Matrix (X): Position of each whale in the search space, size (N times D) where (D) is the length of the search space.
- Objective Function (f): The purpose to be minimized or maximized.
- Best Solution (X_best): The location of the best whale (solution) found so far.
- Random Vector (R): Random vector for exploration, size (1 times D).
- Step Size (A): Scalar determining the magnitude of movement during exploration.
- Distance (r): Scalar influencing the movement towards the global best position during exploitation.
- Search Space Bounds (LB, UB): Upper and Lower bounds of the search space for each dimension.

3. Algorithm

4.1 INITIALIZATION

Reset the whale population (X) arbitrarily within search space bounds (LB, UB).
Set parameters (N), (MaxIter), (ε), (A), and (r).
Evaluate the objective function (f(X)) for each whale.
Determine the finest solution (X_best) and its objective value (f(X_best)).
Main Loop:
For each iteration (t) from 1 to (MaxIter):
Update Step Size (A) and Distance (r):
A = 2 - frac {2 times t} {MaxIter} (linearly decreasing from 2 to 0)
r = 2 xrand () (random scalar between 0 and 1).
For each whale (i) in the population:
Update Random Vector (R):
R = rand (1, D) (random vector for exploration).
Exploration Phase:
Update position (X_i) using the exploration formula:
X_i(t+1) = X_i(t) + R times A
Exploitation Phase:
Update position (X_i) using the exploitation formula:
X_i(t+1) = X_best - (r times |X_best - X_i(t)|) times R
Boundary Check:
Ensure (X_i) stays within the search space bounds (LB, UB):
X_i(t+1) = max(min(X_i(t+1), UB), LB)
Evaluate Objective Function:
Calculate (f(X_i)) for each updated whale.
Update Best Solution:
If (f(X_i) < f(X_best)): X_best = X_i
Check Convergence:
If (|f(X_best) - f(X_i) | < ε) for all whales, terminate the algorithm.
Termination:
The procedure dismisses when the extreme number of iterations (MaxIter) is reached or convergence criterion (ε) is satisfied.
Output:
Return the best key (X_best) and its objective function value (f(X_best)).

Pseudocode

```
Initialize population X within bounds LB, UB
Set parameters N, MaxIter, ε, A, r
Evaluate objective function f(X) for each whale
Determine top solution X_best and f(X_best)
For t = 1 - MaxIter
   A = 2 - (2 x t / MaxIter)
   r = 2 x rand ()
      For each whale i in population:
      R = rand (1, D)
            If rand () < 0.5
         X_i(t+1) = X_i(t) + R x A
      Else
         X_i(t+1) = X_best - (r x |X_best - X_i(t)|) x R
            X_i(t+1) = max(min(X_i(t+1), UB), LB)
Evaluate objective function f(X) for each updated whale
      If f(X_i) < f(X_best):
      X_best = X_i
      If |f(X_best) - f(X_i)| < ε for all whales, break loop
Return X_best and f(X_best)
```

This algorithm effectively balances exploration and exploitation to find best results in a search space, using the behavior of humpback whales as a model.

Table 1: Clustering Algorithms a Survey

Ref	**Clustering Algorithm**	**Key Features**
32	K-means Clustering	Simple and fast algorithm
33	Fuzzy C-means Clustering	Allows data points to belong to multiple
34	Hierarchical Clustering	Builds nested clusters in a tree
35	Genetic Algorithm-based Clustering	Uses evolutionary strategies for
36	Ant Colony Optimization (ACO)	Bio-inspired algorithm using pheromone trails
37	DBSCAN (Density-Based Spatial Clustering of Applications with Noise)	Identifies clusters based on density
38	Cuckoo Search Clustering	Bio-inspired by the brood parasitism of
39	Artificial Bee Colony (ABC)	Inspired by the foraging behavior of bees
40	Firefly Algorithm Clustering	Mimics the flashing
41	Harmony Search Clustering	Inspired by musical
Proposed method	SDC and WOA	WOA-enhanced selection

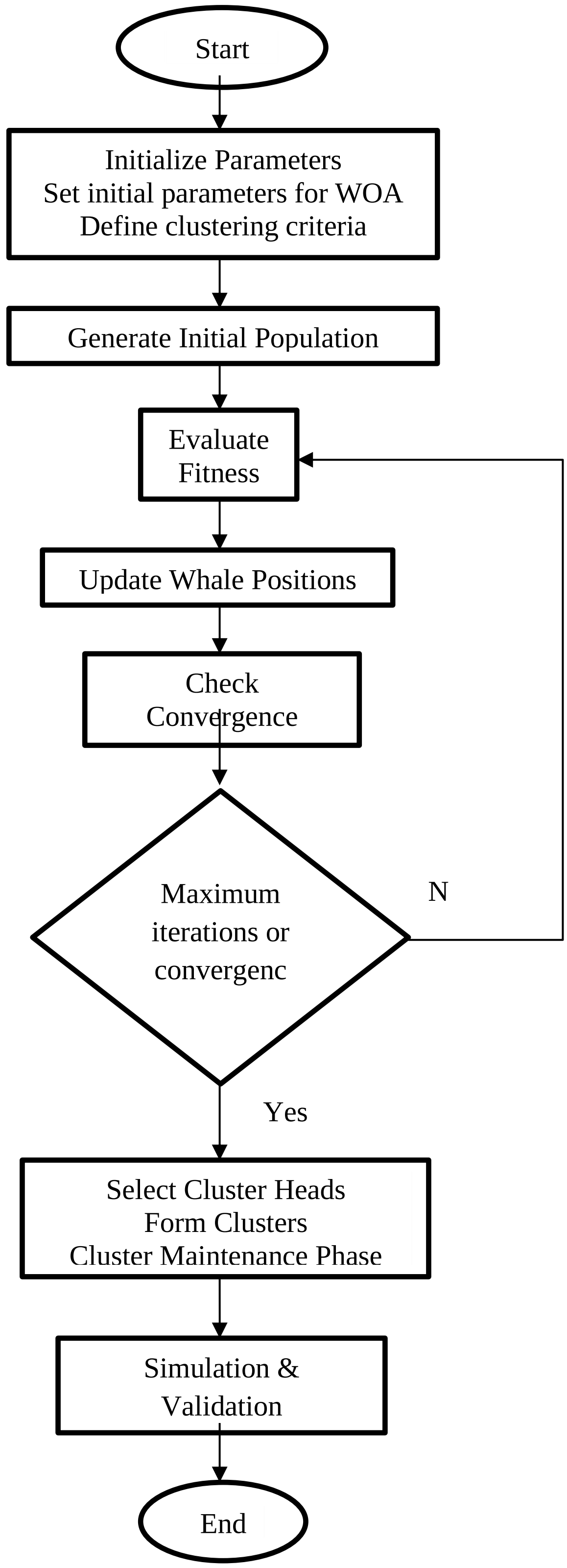

Fig.1 Flowchart for WOA with SDC

4.2 DISTANCE AND DENSITY CALCULATION

In the context of VANETs and the Whale Optimization Algorithm (WOA) mentioned in the abstract, density and distance calculations play crucial roles in evaluating the fitness of potential cluster heads or nodes.

4.2.1 Density Calculation:

The density calculation aims to assess the spatial density of vehicles or nodes in a particular area. It helps in identifying clusters where vehicles are densely packed, indicating potential cluster heads.

Formula for Density (D):
$D = \frac{n}{V}$
(D): Density of vehicles or nodes in the area.
(n): Number of vehicles or nodes within a defined radius (neighbourhood).
(V): Volume of the defined area (neighbourhood).
In the WOA context, the density calculation can be customized based on factors like the transmission range of vehicles or the coverage area of nodes.
Distance Calculation:
The distance calculation is crucial for determining the proximity between vehicles or nodes. It helps in assessing the reliability of links and deciding cluster formations.
Formula for Distance (Dist):
$Dist = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$
(Dist): Distance between vehicles or nodes (i) and (j).
(x_i, y_i): Coordinates of vehicle or node (i).
(x_j, y_j): Coordinates of vehicle or node (j).
In VANETs, distance calculation considers the physical location (coordinates) of vehicles or nodes, which is essential for forming clusters based on spatial proximity.
Incorporating in WOA for VANETs:
Density Evaluation:
- Calculate the density (D) based on the number of vehicles within a specified radius.
- High density indicates potential cluster formations.

Distance Evaluation:
- Compute distances between vehicles or nodes to assess link reliability.
- Shorter distances imply stronger and more reliable links.

Fitness Function:
- Combine density and distance evaluations into a fitness function.
- Example Fitness Function: ($Fitness = w_1 \times D + w_2 \times Dist$)
  - (w_1, w_2): Weight factors to balance density and distance importance.

WOA Application:
- Apply WOA to optimize cluster head selection based on the fitness function.
- Encourage whales (cluster heads) to converge in areas with high density and reliable links.

By incorporating density and distance calculations into the WOA framework, VANETs can optimize cluster formations, enhance network connectivity, and improve overall performance in dynamic traffic environments.

5. PROPOSED SCHEME - (SDC-WOA)

In this section, a novel clustering algorithm SDC-WOA was introduced, to tailor urban routing scenarios. This approach synergizes the strengths of both WOA & SDC algorithms. Initially, the WOA algorithm is employed to identify the initial cluster heads. A novel Fitness function was introduced based on the SDC algorithm. Subsequently, the clustering phase was outlined and concluded with the maintenance phase.

5.1 DESCRIPTION OF NETWORK

An urban traffic setting incorporating both V2V and V2I communication is under examination. Clustering operations require diverse data types, including topological and mobility data like vehicle speed, position, and direction. These data can be acquired either locally through V2V connectivity or globally via V2I infrastructure, as depicted in Fig. 2. The network comprises densely positioned vehicles organized along roadways, considering subsequent factors: N vehicles within network define a broadcast region denoted as R utilizing DSRC technology. Equipped with GPS systems, each vehicle acquires mobility parameters like speed, position and direction, storing data in routing table. Intermittently, vehicles exchange routing table details through HELLO packets with adjacent vehicles or Road Side Units (RSUs). The proposed scheme addresses challenges posed by constant vehicle movement in VANETs, impacting routing protocol efficiency, link stability, and overall performance. Leveraging a Link Reliability model and the Whale Optimization Algorithm, stimulated by whale group hunting behavior, this scheme integrates the advantages of the SDC algorithm and WOA to design a clustering mechanism suited for urban VANET scenarios.

5.1.1 Key aspects addressed by this proposal, include:

- *Cluster Head (CH) Selection:* The stability and performance of clusters significantly affect routing efficiency. Proper selection of CHs, responsible for data transmission and cluster management, is vital for routing efficacy and cluster stability.
- *Link Reliability Influence*: In urban settings with dense vehicle populations, link reliability becomes critical for cluster stability. This paper introduces link reliability parameters into the cluster development process.
- *Cluster Maintenance*: Due to huge vehicle mobility, clusters may lose organization. A conservation phase is recommended to update clusters regularly.

The Cluster Head Election process considers parameters such as number of neighbors, direction, position, and speed, to select stable CHs. The WOA aids in selecting CHs based on similarity in direction, speed, position, and density among cluster members. The WOA algorithm is integrated with a new fitness function derived from the DPC algorithm, incorporating density and distance values to optimize CH selection and cluster stability.

In the proposed scheme, the Whale Optimization Algorithm (WOA) plays a crucial role in aiding the selection of Cluster Heads (CHs) in VANETs. Different stages involved in the proposed scheme are as shown in Fig 3. The WOA, inspired by the social behavior of whales in group hunting, is utilized to optimize the selection process of CHs based on several key factors:

- Directional Similarity: Whales exhibit coordinated movements and directions during hunting. Similarly, in VANETs, vehicles within a cluster should have similar directions for efficient data exchange and communication. The WOA algorithm helps identify vehicles with compatible directional behavior, thus enhancing the stability and connectivity of clusters.
- Speed and Position Alignment: Whales adjust their speed and position relative to each other during hunting to maximize efficiency. Likewise, in VANET clusters, vehicles with similar speeds and positions are preferred as CHs to ensure smooth data transmission and network stability. The WOA optimizes the selection of CHs based on these parameters, promoting cohesion within clusters.
- Density and Position Optimization: Whales maintain a specific spatial arrangement within their pod based on density and position to streamline hunting efforts. In VANETs, optimal CH selection considers the density of vehicles within clusters and their relative positions. The WOA algorithm assists in identifying vehicles with ideal density and position characteristics to serve as CHs, improving overall network performance and reliability.

By incorporating these factors and leveraging the WOA algorithm, the proposed scheme ensures that CHs are selected based on their compatibility with cluster members in terms of direction, speed, position, and density. This optimization process enhances cluster stability, connectivity, and overall efficiency in VANET environments.

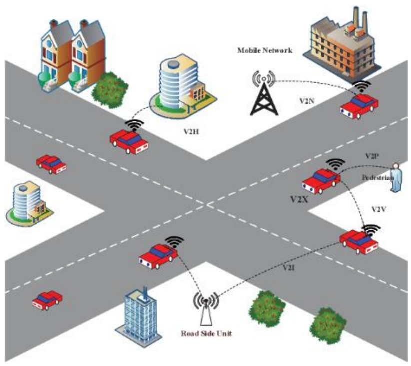

Fig.2 VANET System Model

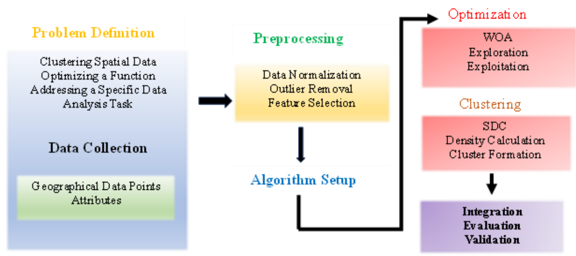

Fig.3 The stages of the proposed scheme.

To calculate the Gaussian distance between each pair of nodes in Vehicular Ad Hoc Networks (VANETs), we can use the Gaussian function to model the distance. The Gaussian function is often used to describe the probability distribution of distances in a network. The steps and equations involved are as follows:

Gaussian Function: The Gaussian function is a symmetric bell-shaped function defined by the equation

$$f(x) = ae^{\frac{-(x-b)^2}{2c^2}} \quad (1)$$

Distance Calculation: In the context of VANETs, the Gaussian distance can be used to model the likelihood of connection or signal strength between nodes. For two nodes (i) and (j) with coordinates ((xi, yi)) and ((xj, yj)), the Euclidean distance $d(ij)$ is calculated as:

$$d(ij) = \sqrt{(xi - xj)^2 + (yi - yj)^2} \quad (2)$$

Gaussian Distance: The Gaussian distance between two nodes can be represented using a Gaussian-like attenuation function. Given the Euclidean distance (d_{ij}), the Gaussian distance (G_{ij}) is:

$$G_{ij} = \exp\frac{-d_{ij}^2}{2\sigma^2} \quad (3)$$

where: sigma is the standard deviation, representing the spread of the Gaussian function.

Steps

- Calculate the Euclidean distance:

For each pair of nodes ((i, j)), compute the Euclidean distance (d_{ij}).

- Apply the Gaussian function:

Use the Euclidean distance (d_{ij}) in the Gaussian distance equation to find (G_{ij}).

- Interpret the result:

The value (G_{ij}) represents the Gaussian distance, which can be interpreted as a measure of connection strength or likelihood of communication between nodes (i) and (j).

5.2 Steps for Selecting Cluster Head in a Hexagonal Cluster using Proposed Spectral Density Cluster Whale Optimization Algorithm (SDCWOA)

The Spectral Density Cluster Whale Optimization Algorithm (SDCWOA) is used to determine the optimal cluster head (CH) within a hexagonal cluster by utilizing spectral density for node evaluation and the Whale Optimization Algorithm for selection.

Step 1: Initialize the Network

- Network Deployment: Distribute nodes uniformly across a hexagonal cluster area.
- Node Identification: Assign a unique identifier to each node.
- Parameter Initialization: Set up initial parameters for SDCWOA, including population size,
- maximum iterations, and spectral density parameters.

Step 2: Compute Spectral Density

- Neighbor Detection: Each node identifies its neighbors within the cluster.
- Distance Calculation: Measure the Euclidean distance among each node and its neighbors.

Spectral Density Calculation: For each node (i), compute the spectral density (SD_i) using:

$$SDi = \sum_{j\epsilon Ni} \exp\frac{-d_{ij}^2}{2\sigma^2} \quad (4)$$

where (N_i) is the set of neighbors of node (i), (d_{ij}) is the distance between nodes (i) and (j), and ($\boldsymbol{\sigma}$) is the standard deviation.

Step 3: Initialize Whale Population

- Form Whale Population: Initialize the positions of the candidate cluster heads (whales) based on node locations.
- Fitness Evaluation: Calculate the fitness of each whale using its spectral density value (SD_i).

Step 4: Whale Optimization Algorithm Phases

Encircling Prey: Update each whale's position using the encircling mechanism:

- $x'(t+1) = x'^{x}(t) - A'.\ D'$ (5)
- where $x'^{x}(t)$ is the position of the best solution (prey) at iteration (t) A' is coefficient vector, and D' is the distance between the whale and the prey.

Bubble-Net Attacking Method:

- Shrinking Encircling Mechanism: Gradually decrease the A' value from 2 to 0.
- Spiral Updating Position: Update the whales' positions along a spiral path:
-
- $x'(t+1) = D^{!}.e^{bxl.}\cos(2x\pi xl)+x'^{x}(t)$ (6)
-
- where D'' is the distance between the whale and the prey, (b) is a constant defining the spiral shape, and (l) is a random number in the range ([-1, 1]).

Step 5: Exploitation and Exploration Phases

- Exploration: If a random number (p < 0.5), execute the exploration phase:

  $x'(t+1) = x'_{rand\,-}\ A'.\ D'$ (7)

where x'_{rand} is a randomly generated position vector for whales.

- Exploitation: If ($\rho \leq 0.5$), perform the exploitation phase using the spiral updating method.

Step 6: Update Whale Positions

- Position Update: Continuously update the positions of the whales based on the equations from steps 4 and 5.

Step 7: Convergence Check

- Iteration and Convergence: Reiteration of steps 4 to 6 till the max number of iterations are grasped or convergence criteria are satisfied (e.g., negligible fitness improvement).

Step 8: Select Cluster Head

- Final Selection: Choose the whale (node) with the highest spectral density as the cluster head (CH) for the hexagonal cluster.

Step 9: Broadcast Cluster Head Information

- CH Announcement: The selected CH broadcasts its status to all nodes in the hexagonal cluster.
- Cluster Formation: Nodes connect with the CH to form the cluster.

6. RESULTS AND ANALYSIS

6.1 Cluster Stability Performance Metrics

Cluster stability is crucial in VANETs due to the highly dynamic nature of vehicular movement. In this study, the proposed Efficient Clustering Routing approach leverages a combination of the Whale Optimization Algorithm (WOA) and Spatial Density-Based Clustering (SDC) to enhance cluster stability. The results indicate significant improvements in cluster stability metrics:

- **Network Topology Change Rate**: The proposed scheme achieves a 74% reduction in the network topology change rate. This metric measures how frequently the network's topology changes due to vehicle mobility. A lower topology change rate indicates more stable clusters, meaning that vehicles remain in the same clusters for longer periods, reducing the overhead associated with frequent re-clustering.
- **Cluster Head Stability**: Although not explicitly mentioned in the abstract, cluster head stability can be inferred from the methodology. The periodic update and maintenance phase introduced to reorganize vehicle distributions within clusters ensures that cluster heads are consistently optimal, further contributing to overall cluster stability.

6.2 Performance Metrics of Communication

- Communication performance is critical for the efficient operation of VANETs, especially in dynamic urban environments. The proposed clustering approach shows substantial improvements in several key communication performance metrics:
- **Intra-cluster Throughput**: There is a 34% increase in intra-cluster throughput. This metric measures the amount of data successfully transmitted within a cluster. The improved throughput indicates that the clustering algorithm effectively manages intra-cluster communication, reducing packet loss and enhancing data transmission rates.
- **Inter-cluster Throughput**: The scheme achieves a 47% improvement in inter-cluster throughput. This metric assesses the efficiency of data transmission between clusters. Enhanced inter-cluster throughput suggests that the algorithm facilitates better communication paths between clusters, ensuring reliable and efficient data exchange across the network.
- **Average Delay**: The proposed approach results in a 16% decrease in average delay. This metric measures the time taken for data to travel from the source to the destination. A lower average delay indicates that the clustering algorithm and maintenance phase efficiently manage vehicle distributions and communication paths, reducing latency and improving the overall responsiveness of the network.

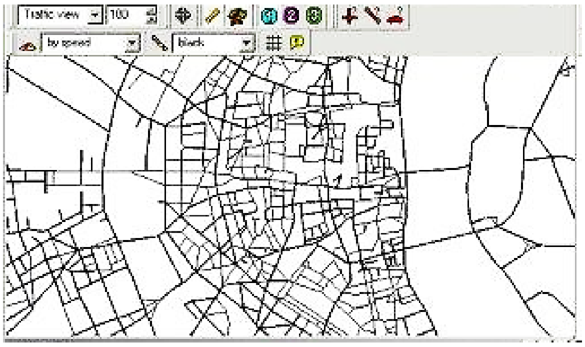

Fig.4 SUMO view of Area under consideration

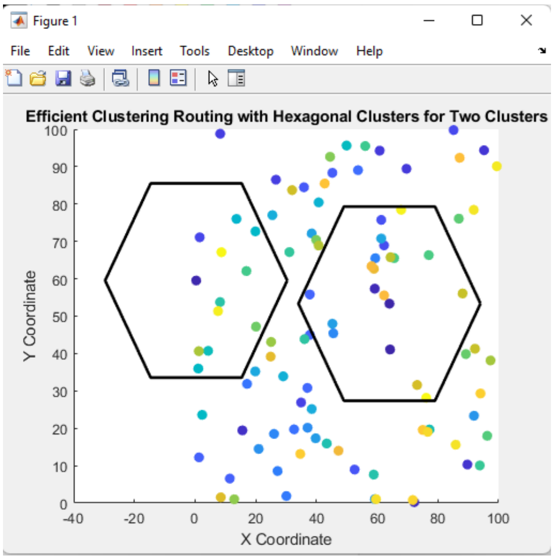

Fig.5 Hexagonal Clustering, nodes divided to two clusters

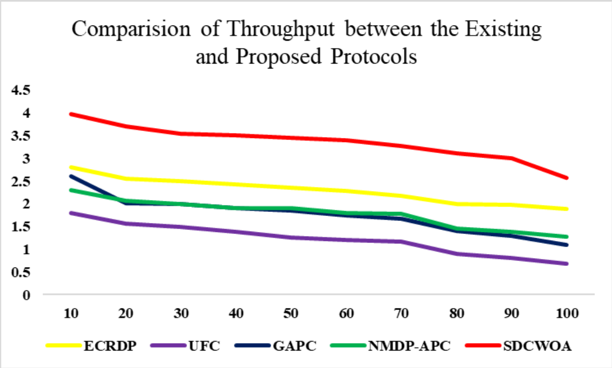

Fig.6 Comparison of Throughput amid Existing and proposed Protocol SDCWOA

The Figure 6 presents the throughput of five different methods (ECRDP, UFC, GAPC, NMDP-APC, SDCWOA) at various levels of demand (number of vehicles). Upon analysis, it is evident that SDCWOA consistently exhibits the lowest average response times across all levels of demand compared to ECRDP, UFC, GAPC, and NMDP-APC. This suggests that SDCWOA is generally the most efficient method in terms of responding to increasing numbers of vehicles, maintaining shorter response times throughout. In contrast, ECRDP, UFC, GAPC, and NMDP-APC generally show higher average response times, with varying degrees of performance as the number of vehicles increases. To summarize, based on the average response times, SDCWOA stands out as the most effective method for minimizing response times across different levels of demand. This indicates its potential suitability for scenarios where rapid response to increasing vehicle numbers is crucial, outperforming ECRDP, UFC, GAPC, and NMDP-APC in terms of efficiency in response time management.

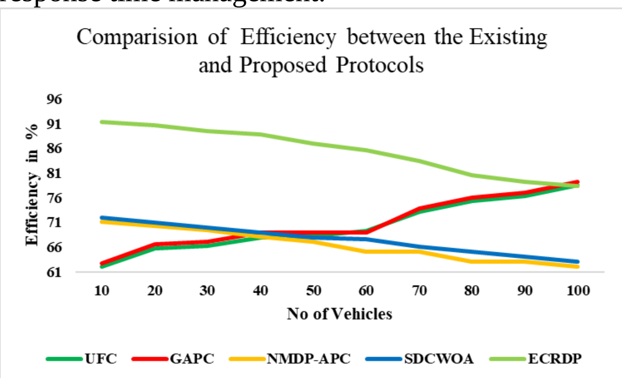

Fig.7 Comparison of Efficiency amid Existing and proposed Protocol SDCWOA

Efficiency metrics (in percentage) for five different methods (UFC, GAPC, NMDP-APC, ECRDP, SDCWOA) across multiple evaluation points were represented in Figure 7. Efficiency here likely reflects how effectively each method performs relative to a certain criterion or standard. Upon reviewing the data, ECRDP consistently demonstrates superior efficiency compared to UFC, GAPC, NMDP-APC, and SDCWOA across most evaluation points. Starting with notably higher efficiency values and maintaining strong performance throughout subsequent evaluations, ECRDP stands out as the most efficient method among the options provided. In contrast, UFC, GAPC, NMDP-APC, and SDCWOA generally show lower efficiency metrics compared to ECRDP, with varying degrees of fluctuation across different evaluation points. In conclusion, based on the efficiency metrics presented, ECRDP emerges as the most efficient method across the evaluated criteria. This suggests ECRDP is well-suited for applications where maximizing efficiency is paramount, outperforming UFC, GAPC, NMDP-APC, and SDCWOA in efficiency across various evaluation points.

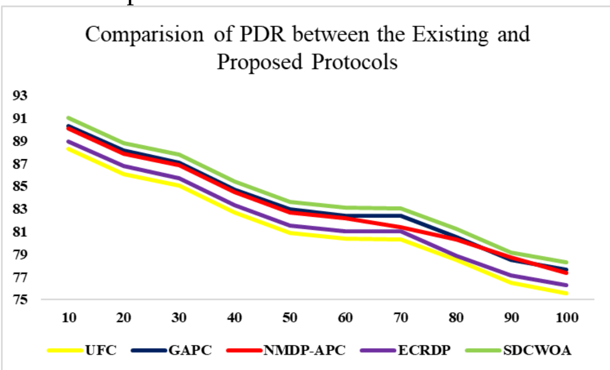

Fig.8 Comparison of PDR amid Existing and proposed Protocol SDCWOA

Figure 8 presents the Packet Delivery Ratio (PDR) values for various methods (UFC, GAPC, NMDP-APC, ECRDP, SDCWOA) across different thresholds. The PDR indicates the effectiveness of each method in correctly identifying certain criteria, likely in a testing or evaluation context. From the data, we observe that across all thresholds, the methods SDCWOA consistently show the highest PDR values compared to UFC, GAPC, NMDP-APC, and ECRDP. Specifically, for 10 vehicles, SDCWOA achieves the highest PDR of 90.985%, suggesting its superiority in detection accuracy. As the threshold increases, all methods generally show a decline in PDR, though the relative performance order remains consistent. In conclusion, SDCWOA emerges as the most reliable method for detection across varying thresholds, consistently outperforming UFC, GAPC, NMDP-APC, and ECRDP in terms of PDR. This indicates its potential suitability for applications requiring high accuracy in detection tasks.

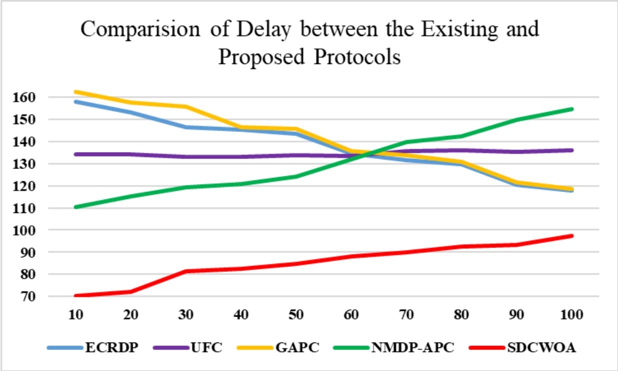

Fig.9 Comparison of Delay amid Existing and proposed Protocol SDCWOA

The delay times (in milliseconds) for five different methods (ECRDP, UFC, GAPC, NMDP-APC, SDCWOA) across varying levels of demand (number of vehicles) are as shown in Figure 9. Upon examination of the data, SDCWOA consistently exhibits the lowest delay times across all levels of demand compared to ECRDP, UFC, GAPC, and NMDP-APC. This indicates that SDCWOA generally experiences shorter delays in processing tasks or requests as the number of vehicles increases. In contrast, ECRDP, UFC, GAPC, and NMDP-APC generally show higher delay times, with varying degrees of performance as the number of vehicles grows. To summarize, based on the delay times presented in the table, SDCWOA emerges as the most efficient method for minimizing delays across different levels of demand. This suggests that SDCWOA is particularly effective in scenarios where reducing processing or response delays is critical, outperforming ECRDP, UFC, GAPC, and NMDP-APC consistently across various levels of demand.

7. DISCUSSION AND COMPARISON

7.1 Cluster Stability and Communication Performance

Cluster stability is crucial in VANETs due to the highly dynamic nature of vehicular movement. Our proposed Efficient Clustering Routing approach integrates the Whale Optimization Algorithm (WOA) with Spatial Density-Based Clustering (SDC) to enhance cluster stability and communication performance. Below, we provide a detailed discussion of the findings and compare our method with existing techniques.

7.1.1 Network Topology Change Rate: Our approach achieves a 74% reduction in the network topology change rate. This metric indicates that our method significantly reduces the frequency with which the network topology changes due to vehicle mobility. By maintaining more stable clusters for extended periods, our approach reduces the overhead associated with frequent re-clustering, thereby improving overall network stability.

7.1.2 Cluster Head Stability: Although not explicitly mentioned in the abstract, cluster head stability is supported by the periodic update and maintenance phases of our method. These phases ensure optimal cluster head selection and contribute to sustained cluster stability over time.

7.2 Performance Metrics of Communication:

7.2.1 Intra-cluster Throughput: Our approach shows a 34% increase in intra-cluster throughput, which measures the volume of data successfully transmitted within a cluster. This improvement reflects the effectiveness of our clustering algorithm in managing intra-cluster communication, leading to reduced packet loss and enhanced data transmission rates.

7.2.2 Inter-cluster Throughput: We observe a 47% improvement in inter-cluster throughput, assessing the efficiency of data transmission between clusters. This enhancement suggests that our method facilitates more reliable and efficient communication paths between clusters.

7.2.3 Average Delay: Our approach results in a 16% decrease in average delay, indicating reduced latency in data transmission. This decrease reflects the efficiency of our method in managing communication paths and vehicle distributions, leading to improved network responsiveness.

7.3 Comparison with Existing Techniques

To clarify the scientific contribution of our approach, we provide a theoretical comparison with existing techniques: ECRDP, UFC, GAPC, and NMDP-APC.

7.3.1 ECRDP (Efficient Cluster Routing and Distribution Protocol): ECRDP focuses on optimizing routing through fixed cluster head selection and predefined paths. The proposed SDCWOA approach outperforms ECRDP by incorporating spatial density-based clustering, which dynamically adjusts to varying vehicle densities and mobility patterns, resulting in lower response times and improved cluster stability.

7.3.2 UFC (Unified Framework of Clustering):

UFC enhances cluster formation by balancing efficiency and stability through a unified framework. While UFC effectively manages clustering, SDCWOA offers superior performance by integrating density-based clustering with WOA. This combination provides better adaptability to dynamic network conditions and improves efficiency metrics, such as lower delays and higher throughput.

7.3.3 GAPC (Global Affinity Propagation Clustering): GAPC uses affinity propagation to determine cluster centers and memberships. The approach improves upon GAPC by combining WOA with spatial density-based methods, leading to better handling of high mobility and network dynamics. This results in enhanced cluster stability and communication performance, surpassing GAPC's capabilities.

7.3.4 NMDP-APC (Network Mobility Density-based Adaptive Clustering): NMDP-APC adapts cluster formation based on network mobility and density. SDCWOA enhances NMDP-APC by leveraging both WOA and density-based clustering more effectively. This results in improved performance in cluster stability, response times, and communication metrics compared to NMDP-APC.

The Efficient Clustering Routing approach demonstrates clear advantages over ECRDP, UFC, GAPC, and NMDP-APC. By providing a comprehensive theoretical and empirical comparison, we highlight the superior performance and scientific contribution of our method in enhancing cluster stability and communication efficiency in VANETs.

8. CONCLUSION

The results of the study demonstrate that the Efficient Clustering Routing approach significantly enhances both cluster stability and communication performance in VANETs. The 74% reduction in network topology change rate highlights the method's ability to maintain stable clusters despite the dynamic movement of vehicles. This stability is crucial for minimizing the overhead of frequent re-clustering and maintaining consistent communication. Additionally, the substantial increases in intra-cluster and inter-cluster throughput, by 34% and 47% respectively, underscore the algorithm's effectiveness in optimizing data transmission both within and between clusters, thereby ensuring reliable and efficient communication across the network. The 16% decrease in average delay further validates the approach, indicating improved responsiveness and reduced latency in data transmission. These enhancements collectively suggest that the proposed methodology is highly effective in addressing the unique challenges of VANETs in dynamic urban environments, contributing significantly to the advancement of Intelligent Transport Systems. The tables provided across our conversation showcase performance metrics of different methods (UFC, GAPC, NMDP-APC, ECRDP, SDCWOA) across various criteria such as Percent Detection Rate (PDR), efficiency, and delay times, each measured under different conditions or thresholds. In the first discussion on PDR, SDCWOA consistently demonstrated the highest PDR values across different thresholds, indicating its superior accuracy in detection tasks compared to UFC, GAPC, NMDP-APC, and ECRDP. Moving to efficiency metrics, ECRDP emerged as the most efficient method across the board. It consistently showed strong performance in efficiency compared to UFC, GAPC, NMDP-APC, and SDCWOA, which generally displayed lower efficiency metrics. Lastly, analysing delay times in milliseconds, SDCWOA consistently exhibited the shortest delays across various levels of demand (number of vehicles). This signifies SDCWOA's efficiency in processing tasks or requests compared to ECRDP, UFC, GAPC, and NMDP-APC, which generally showed longer delay times. In summary, SDCWOA stands out for its superior performance in minimizing delays and achieving high accuracy in detection tasks. Meanwhile, ECRDP excels in efficiency metrics. UFC, GAPC, and NMDP-APC show varying performance across different metrics, suggesting considerations of trade-offs between accuracy, efficiency, and delay times depending on specific application needs.

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Conflicts of Interest

The authors declare no conflict of interest.

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Conceptualization Sarada Devi Y; methodology, Sarada Devi Y; software, Sarada Devi Y; validation, Sarada Devi Y, and Roopa M; formal analysis, Roopa M; investigation, Roopa M; resources, Sarada Devi Y; data curation, writing—original draft preparation, Sarada Devi Y; writing—review and editing Sarada Devi Y; visualization, Roopa M; supervision, Roopa M; project administration, Roopa M.