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RESEARCH ARTICLE

Vehicular Ad Hoc Networks Assisted Clustering Nodular Framework for Optimal Packet Routing and Scaling

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Abstract – Wireless communication between moving cars and stationary structures is made possible by Vehicular Ad Hoc Networks (VANETs). The goal is to communicate traffic data so that accidents can be avoided and resources can be used most effectively in current traffic conditions. There are several methods for enhancing VANETs' communicative efficacy; one is clustering in-vehicle networks. One CH assigned to each cluster and is in charge of the cluster as a whole. The CHs are responsible for all communications, both those between clusters and those within a single cluster. Vehicles in this study are organized into groups called clusters and information is relayed from one CH to another. Several different routing algorithms may be used to send data from one vehicle to another to improve the network's performance as a whole. Many reliable and safe routing systems for VANETs have been presented in the past decade. These protocols have several drawbacks, including their complexity, inability to scale to extensive networks, increased transportation costs, etc. Several bio-inspired strategies for optimal packet routing among vehicle nodes have been proposed to overcome these restrictions. Hence, this paper presents the efficient optimization of vehicular ad hoc networks assisted by a clustering nodular [EO-CN] framework to solve the abovementioned issues. The proposed method drastically reduced network overhead in settings with varying densities of nodes. Numerous experiments were conducted with various parameters, including cluster size, network area, node density, and transmission distance. These findings demonstrated that [EO-CN] performed better than competing approaches.

Index Terms – Clustering, Efficiency, Optimization, VANET, Nodes, Transportation.

1. INTRODUCTION

The benefits of wireless networks, including portability, security (using the most recent Wi-Fi encryption techniques), efficiency (thanks to the ability to scale), cost-effectiveness, etc., have made this an increasingly popular field [1]. Wireless networks can be broken down into two broad categories: those that are permanently installed, or "infrastructure," and those that are temporary, or "ad hoc," in nature [2]. The possibility of distinguishing between mobile and vehicle ad hoc network allows for additional classification of ad hoc networks [3]. Hybrid VANETs combine features from both V2V and V2I networks, whereas V2I VANETs bridge the gap between mobile devices and fixed infrastructure [4]. In this research, we analyze the data and conversations in a VANET or a network comprised entirely of automobiles [5]. For the Intelligent Transportation System (ITS) sake, vehicles exchange data through a network of interconnected nodes that can send, receive, and reroute messages [6]. The well-known Intelligent Transportation System (ITS) can contribute to better road safety by facilitating the sharing of traffic information via mobile and wireless networks [7].

Vehicle safety, collision avoidance, traffic monitoring, traffic flow management, route recalculation and blind intersection detection in real-time are all safety-related ITS applications [8]. However, a wide range of non-safety-related applications fall under the general heading of Intelligent Transportation Systems (ITS) including location-based services (like finding the closest gas station, eatery, or accommodations), autonomous cost payment, and IT solutions (like offering Internet access) [9]. The initial vehicle networks that could serve ITS applications were V-WLANs and VCNs, which stood for vehicular wireless local area networks and vehicular cellular networks, respectively [10]. the nodes that make up a V-WLAN are strategically located at heavily populated areas. A virtual cell network, on the other hand, is made up of permanent cellular gateways, such as 3G/4G LTE base stations, which offer wireless communication across regions called "cells" [11]. Another major issue of infrastructure-based vehicular networks is the expense of deploying several permanent units and gadgets at the road's periphery [12].

Because of these limitations, vehicular networks require all participating for use in multi-hop and unicast routing in conjunction with both mobile nodes and fixed gateways [13]. Consequently, a novel form of vehicular network known as a vehicular ad hoc network (VANET) has been proposed to guarantee precise and pervasive connectivity for road users. This enhances the systems within cars and opens the door for ITS applications in terms of network reliability and access, allowing for the deployment of primarily on-board equipment. The expense of communication is low [14].

An example of a particular case of MANETs is the vehicular ad hoc network (VANET), & includes both moving (vehicles) and stationary (roadside) nodes [15]. Digital information can be shared between vehicles and RSUs thanks to technologies like Inter-Vehicle Communication (IVC) and Vehicle-to-Roadside Communication (VRC) [16]. Due to their restricted ability to change course and speed, VANET vehicles adopt a structured mobility paradigm with specific changes for the purpose of adjusting to new settings.

The smart gadgets (bits) that make up Wireless Sensor Networks rely on their periphery as nodes. Wireless communication terminals with processing units, such as those equipped with transceivers, are small, lightweight, and capable of performing various activities. VANETs are a variant of MANETs that deviate from the standard in ways such as Shifting Patterns, Limited Power, and Flexibility of Movement. When considering the necessity of new approaches to combining next-generation wireless networks with automobiles, various potential applications in VANETs are becoming apparent. VANET is being used as a communication backbone to share data on traffic conditions and control data from multiple applications. Among these applications are the following: medical monitoring during emergencies, audio-sound pollution monitoring, urban emission monitoring, and traffic congestion prediction and control. [16].

One primary goal is to analyze the clustering problem in VANETs from the standpoint of existing approaches and their variations. The goal of this work is to create a reliable and clever clustering strategy for VANETs.

The study's key findings are as follows:

- Optimal packet routing among vehicle nodes has been created; however, problems like rising transportation costs, complicated networks, and a lack of scalability have prompted the development of Efficient Optimization of Vehicular Ad hoc Networks by Clustering Nodes [EO-CN].
- The above method drastically reduced network overhead in settings with varying density of nodes.
- Several experiments were run with varying values of cluster size, network area, node density, and transmission distance, among many other variables and it is clear that [EO-CN] outperformed alternative methods.

The paper will have the following structure: Section 1 provides an overview of VANET, while Section 2 discusses related environment research. In case of a node or car breakdown network, EO-CN proposes the clustering method of communication between vehicles, as described in Section 3. The article summarizes with figures and a discussion of the research's significance in sections 4 and concludes in section 5.

2. RELATED WORK

With the help of efficient clustering networks, virtual agents, evolutionary algorithms, and artificial neural systems facilitate program creation and educated judgments. A lot of ground has been made in this area in recent years. Currently, no standardized, app- and node-independent framework for integrating brains into IoT-enabled sensors exists.

For optimal cluster head selection, Ahsan, W. et al. (2019) [17] VANET node clustering algorithm based on optimization (GOA) was implemented by the grasshoppers. The proposed approach decreased network overhead in cases of variable node density. Several trials were run to compare GOA's performance in comparison to cutting-edge methods such as ACO, GWO, and the dragonfly algorithm.

A New Clustering Algorithm for VANETs (CAMONET) based on Moth-Flame Optimization (MFO) developed by Shah, Y. A. et al. [18] an algorithm motivated by the natural world which is CAMONET creates clusters that are tailored for robust transmission. Three different particle swarm optimization algorithms—Multi-Objective Particle Swarm Optimization (MOPSO), Clustering Algorithm Based on Ant Colony Optimization for VANETs (CACONET), and Comprehensive Learning Particle Swarm Optimization (CLPSO)—are employed to conduct experimental evaluations of CAMONET. The relative effectiveness of different algorithms is evaluated by a large number of experiments. By modifying the grid size, number of nodes, and node range of transmission of the network, the intended results can be attained. Clustering at its best requires thinking about the velocities, orientations, and transmission ranges of the nodes.

The unique optimization method Whale Optimization Algorithm for Clustering in Vehicular Ad hoc Networks (WOACNET) was presented by Husnain, G. [19] takes into

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factors as the density of nodes, velocity, direction, and size of the grid while clustering. To determine the most capable and knowledgeable candidate for the cluster head (CH) role, we reexamined the calculations and evaluations made in the original implementation of the WOACNET. After running simulations, extensive experiments were carried out on WOACNET. Modern, well-established models were used to assess the model's efficacy. Alternatives like Grey Wolf Optimization (GWO) and Ant Lion Optimization (ALO).

Bitam S. et al. [20] elucidated the VANET setting's use of routing techniques inspired by biological networks. Different bio-inspired strategies for optimizing the routing of packets between vehicular nodes have been proposed to deal with these constraints. Specifically, we compare these algorithms across several dimensions and outline their salient characteristics, strengths, and limitations. We propose an integrated formalization of the various biologically-inspired multi-modular approaches to VANET routing. Improving road safety relies mainly on this network's ability to reliably and promptly disseminate information among its vehicle nodes. There have been numerous proposals for routing protocols in VANETs during the past decade that can meet reliability and safety standards. Complexity, inability to scale to extensive networks, routing overheads, etc., are a few problems with these protocols.

Husnain introduced comprehensive learning PSO (CLPSO) and Multi-Objective PSO (MOPSO), Ghassan Husnain. et al. [21], and compared the VANET setting with regards to dimensions such as transmission distance, cluster density, node count, and grid size. The present research uses V2V VANETs to enhance motor vehicle-to-motor vehicle interaction. Streamlining traffic data coordination is the target so that accidents can be avoided and resources can be used most effectively given the current traffic conditions—the communication between vehicles has a wide range of difficulties, some of which can be overcome through clustering. The vehicles in this research are grouped into clusters, relaying information from one CH to another. Different routing algorithms may be used to distribute data across vehicles to maximize the network's efficiency.

Using the Trust methodology amongst low-cost WSN nodes, Rami Ahmad et al. [22] presented a method dubbed Trust-Cluster Head (Trust-CH) that aids in balancing energy consumption and security. The degree of security, the number of repeats, and the behavior of packet transmission are monitored to build trust between nodes. The suggested methodology improves upon previous studies in extending the lifetime of networks by 40% and reduces power consumption by up to 28% when a static encryption scheme is used.

An improved cluster-based lifetime protocol called ECBLTR is suggested by Afia Naeem et al. [23], aiming to increase the network's average throughput and routing stability. Considerations such as concentration, the cluster head is evaluated using the Sugeno model fuzzy inference system, which takes into account local separation, nodes level, residual power, and proximity to the base station. (CH). Our enhanced routing protocol proves, for a fixed network size, that VANET link performance is enhanced by a good circuit model and a successful routing protocol.

Clustering is one approach that can improve VANETs' dependability and scalability. The benefits of vehicle clusters extend far beyond mere routing aid and include, for example, the identification of congestion, the development of entertainment applications, and the dissemination of information. Traditional methods such as GOA, CAMONET, WOACNET, VANET, and CLPSO have been proposed as a safe and effective approach to optimize achievement ratio and other criteria; information on energy utilization is provided. This article provides a high-level summary of the suggested model.

2.1. Problem Statement

The VANET network has to be more stable and have its average throughput increased in both directions. When no base station is available, routing becomes a major challenge in a VANET, which is inherently dynamic. Reduced network lifespan is caused by imbalanced energy usage. Reduced network efficiency is the result of the network's instability. There must be a routing system in place that can group nodes together, keep power consumption constant, and make the network last longer. The suggested method aims to improve routing stability and average throughput (in VANET) by tackling these issues. The following table 1 shows the comparison between the existing methods.

Table 1 Comparison between the Existing Methods

Reference No	Author Name	Inferences	Limitations
17	Ahsan, W. et al. (2019)	The proposed approach decreased network overhead in cases of variable node density.	Several trials were run to compare GOA's performance to cutting-edge methods such as ACO, GWO, and the dragonfly algorithm for optimization.
18	Shah, Y. A. et al.	An algorithm motivated by the	The desired outcomes can be achieved by adjusting

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		natural world, CAMONET, creates clusters tailored for robust transmission.	the network's grid dimensions, quantity of nodes, and transmission distance between nodes.
19	Husnain, G. et al	To determine the most capable and knowledgeable candidate for the cluster head (CH) role, we reexamined the calculations and evaluations made in the original implementation of the WOACNET.	After running simulations, extensive experiments were carried out on WOACNET.
20	Bitam S. et al.	Improving road safety relies mainly on this network's ability to reliably and promptly disseminate information among its vehicle nodes.	Complexity, inability to scale to extensive networks, routing overheads, etc., are a few problems with these protocols.
21	Ghassan Husnain. et al.	The goal is to coordinate traffic data so that accidents can be avoided and resources can be used most effectively given the current traffic conditions—the communication between vehicles has a wide range of difficulties, some of which can be overcome through clustering.	Different routing algorithms may be used to distribute data across vehicles to maximize the network's efficiency.
22	Rami Ahmad et al.	The degree of security, the number of repeats, and the behavior of packet transmission are monitored to build trust between nodes.	Even though the suggested paradigm is resilient to a plethora of network assaults
23	Afia Naeem et al.	The cluster head (CH) is assessed using the Sugeno model fuzzy inference system, which takes into account factors including focus, local distance, node level, leftover energy, and proximity to the base station.	All of the network's nodes must use secure clustering to communicate with one another.

3. PORPOSED MODELLING

3.1. Efficient Optimization of Vehicular Ad Hoc Networks by Clustering Nodes [EO-CN]

An increasingly popular form of networking, Vehicular Ad hoc Networks (VANETs) are seeing increasing application in a variety of industries, such as transportation, media, finance, and more. To reduce the amount of unpredictability in VANETs' clustering, an Efficient Optimization of Vehicular Ad hoc Networks by Clustering Nodes is proposed in this section. This algorithm considers spread distance, number of nodes, velocity, heading, and grid size, they are all involved in the process of clustering. To reduce the amount of unpredictability in VANETs' clustering, an Efficient Optimization of Vehicular Ad hoc Networks by Clustering Nodes is proposed in this section.

Clustering is used to improve VANETs' transmission via several hops. Since nodes in VANETs vary in terms of characteristics like memory requirements and power consumption, addressing issues like QoS can be complex. It is possible to categorize algorithms as cross-layer transmission practices, quality-of-service transmission rules, or cluster-based channeling rules. Any network protocol that uses clusters as a fundamental building block is considered a cluster-based routing protocol. The system's mapped clusters organize all of the network's vehicles. In a cluster network, one node is tasked with gathering data from all of the cars in

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its region before sending it to the other nodes in the network, known as "sinks."

Vehicle network cluster optimization problems are NP-hard and can be tackled with metaphor, natural metaheuristics, and other bio-inspired techniques. The clustering algorithms are a crucial part of many of the CBR approaches. Clustering is the process of solving a set of related problems at once. Ad-hoc network routing is significantly affected by these MOPS. Multiple metrics, such as Packet Delivery Ratio (PDR), Bandwidth utilization, and Average End-to-End Delay (AE2ED), affect the traditional QoS's overall performance. Cluster optimization entails minimizing the number of clusters, updating each vehicle's cluster head, forming clusters of the optimal size, determining the optimal size of the clustering degree, reorganizing clusters, and selecting CHs.

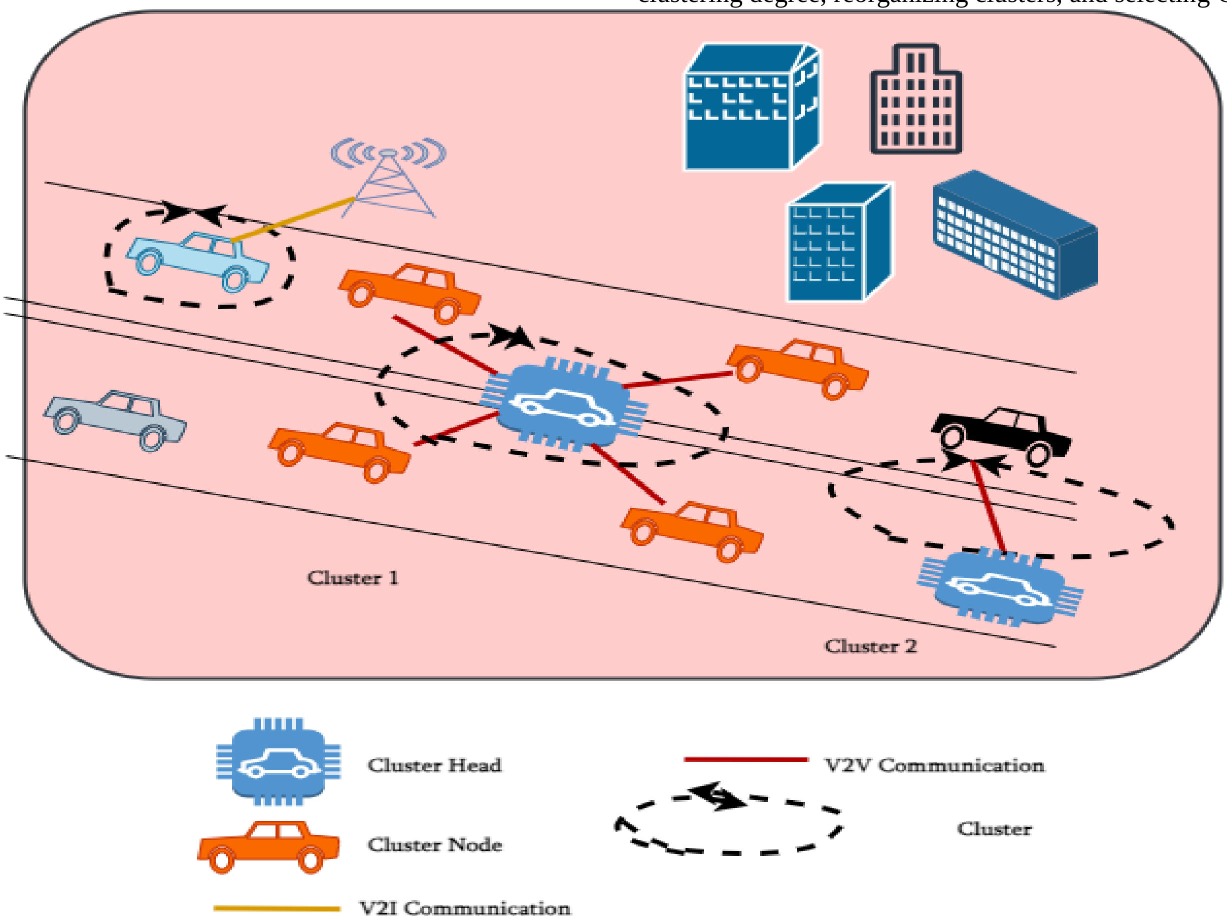

Figure 1 Vehicle Ad-Hoc Network Node Clustering

In above Figure 1 shows that each node in a VANET is part of at least one cluster that works together to manufacture vehicles. Those methods determine which node in the cluster will serve as the leader. It is the responsibility of the cluster head to ascertain the maximum number of terminals that a cluster can have and dividing up the available network resources among them. A cluster leader must maintain the network topology by growing the cluster to an optimal size. However, due to the erratic movement of cars, a consistent topology inside the cluster is challenging to preserve. Neighbours are members of the same cluster that are physically close to one another and fall within the cluster head's transmission range. The relevance of Vehicular Ad hoc Networks (VANETs), an essential network type, cannot be overstated in fields as diverse as traffic management, use in the media, safe financial transactions, etc.

These are the streamlined optimization tasks that contribute to cluster reliability. Optimizing a cluster's performance is an np-hard challenge; however, it is possible to use metaheuristics, particularly bio-inspired optimization techniques, to solve this challenge. For VANETs, the authors provide an AI-based clustering technique that takes into account CN speed, cluster size, and network density to enhance traffic flow and navigation. This algorithm employs a virtual area network (VANET) in its quest for an optimum CH amount and lengthy cluster life, contributing significantly to network stability. The moth's localization and planned abilities utilizing the decreasing feature are applied to improve placement, increasing the possibility of collecting CHs and decreasing the group's amount in a given network.

$$\emptyset_k = S_k + FG_k + AD_k \quad (1)$$

In the above equation (1) $\emptyset_k$ be the vehicle's vantage point of kth agent, S_k is the social attraction constant, FG_k be the pressure of gravity of the kth agent, AD_k is the air drift variable.

$$S_k = \sum_{l=1}^{n} s(d_i) * D \quad (2)$$

In the above equation (2) where d_i denotes the distance, D is the multiplication factor, S_k be the social attraction factor.

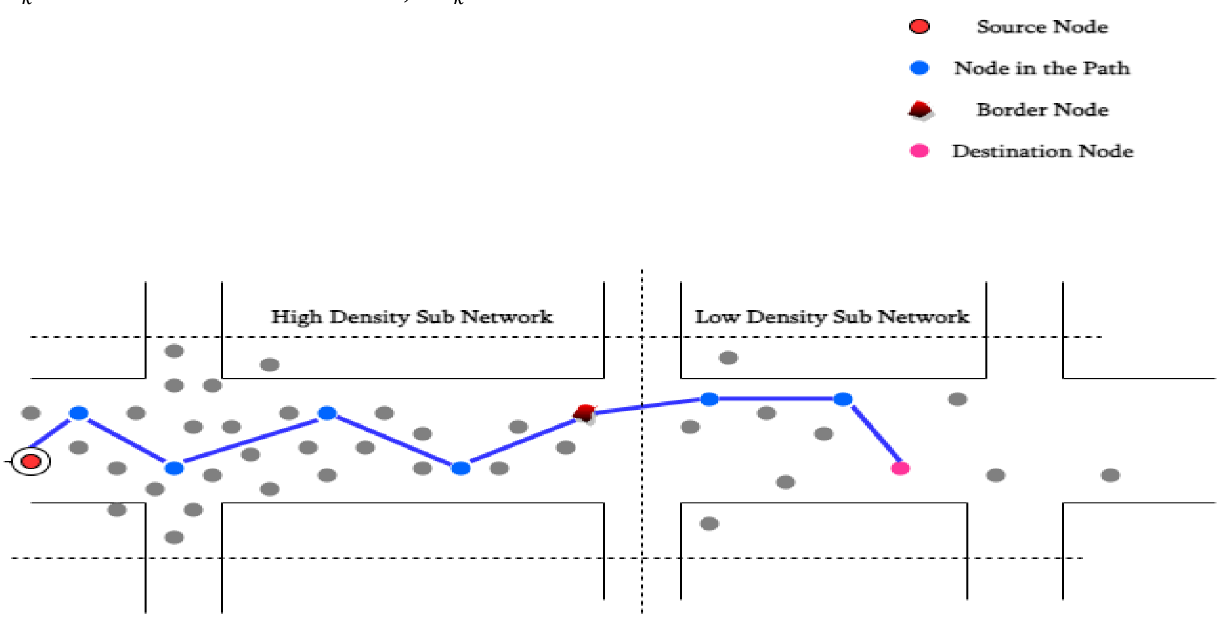

Figure 2 Network Density-based Transmission

When it comes to VANET safety applications, it is crucial that severe standards be met, and EO-CN, as a protocol for both single-cast and multi-path connectivity, does that. Figure 2 depicts the transition from a topology-based routing procedure to a geography-based routing procedure that occurs as part of a hybrid routing protocol in dense networks such as city-based VANETs. It's important to note that EO-CN can use a threshold to differentiate between high and low network densities in VANET and use either a topology-based or a geography-based method. The topological method was motivated by the way bees communicate with one another during foraging. Forward scouts are route request packets generated, replicated, and transmitted from the sending node to some of the receiving nodes' neighbors.

When a node reaches its final neighbor, it performs the same operation until it either reaches its final finds its way there or comes across a node that can direct it to its last neighbor. A pathway reply (a "reversed scout") is produced and returned over the identical route to the first transmitting node it came from if the path is found. Remembering that there may be more than one way to transmit a message is essential. Regarding the geographical method, the optimum route is chosen from several formed by inserting the location of network nodes into a genetic algorithm. After choosing two parents, it performs a two-point crossover to produce two offspring. A two-point mutation operator allows for mutations to be introduced to all progeny. This process is repeated until the best possible solution is found. The authors have run scenarios with different population densities and vehicle speeds using an accurate transportation model. There was an improvement in the packet delivery ratio and a reduction in the delay from end to end.

In Figure 3 shows that below all of the nodes in the network are given the same set of static weights based on factors such as node ID and transmission distance that are used to determine which CH to use. It employs static weights, yielding the same result across varying network configurations. This approach does not rely on control channel information like the passive clustering process used in the protocol for passively supported clustered routing for vehicle ad hoc networks. Clustering relies on the data contained within each data packet. In many respects, its performance is on par with the passive clustering technique it replaced, yet the network's efficiency has not been improved.

Similarly, there are optimization issues for different kinds of communication that plague all traditional systems. These issues are classified as NP-hard or non-convex and evolutionary algorithms excel at finding solutions to them

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since nature inspires them. The research presented herein offered an approach for clustering vehicular nodes. This method improved the clustering process by taking into account a wide variety of factors (node weight and transmission range among others). The overall number of clusters in each scenario is determined through mathematical modelling of the behavior, which focuses primarily on the interplay of social attraction and repulsion.

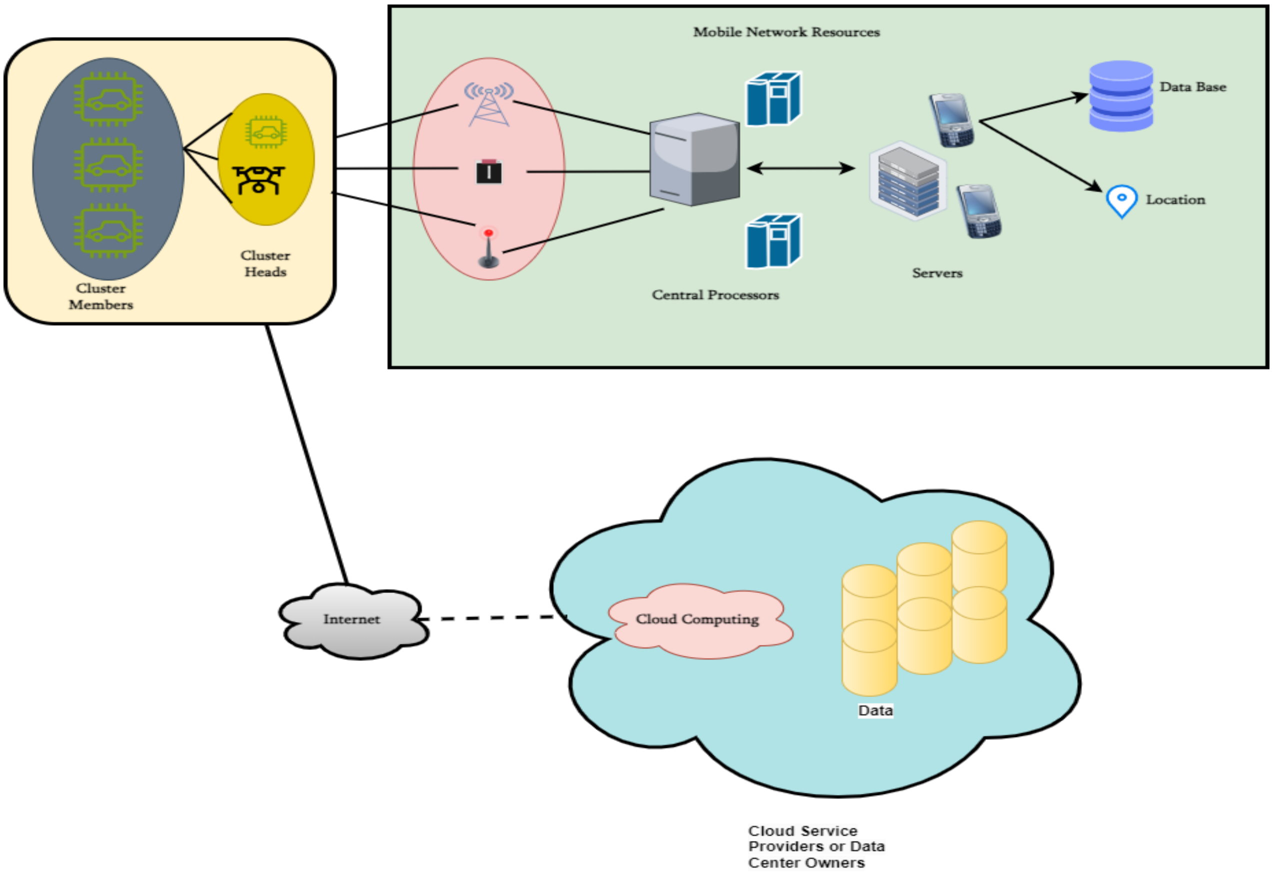

Figure 3 Wireless Drone Assisted Architecture of VANET

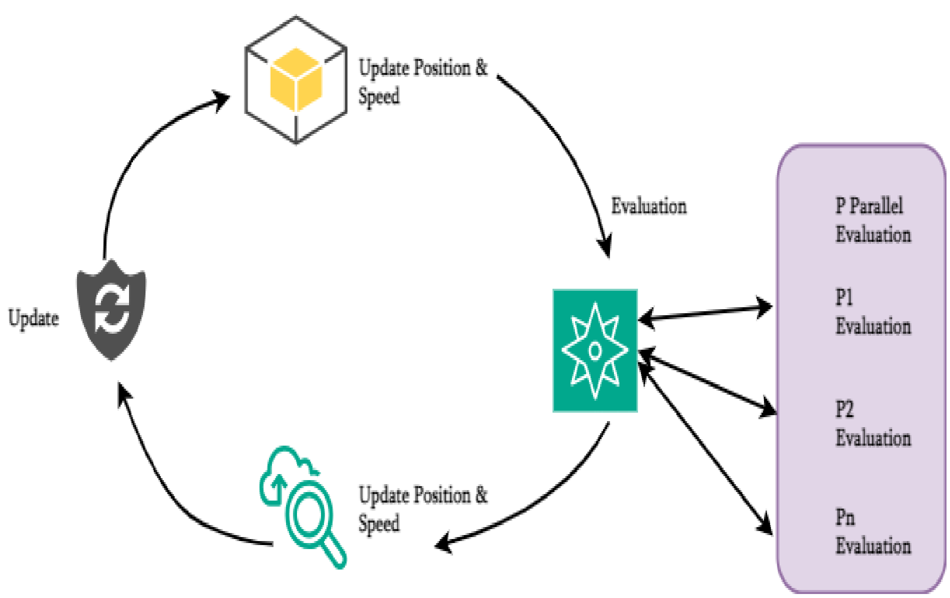

Figure 4 Parameterization Improvement for the EO-CN

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Parameterization Improvement for the EO-CN is depicted in the figure 4 as shows that above Optimization has sparked several research projects to enhance internet connectivity and the VANET routing system. In this section, we discuss the multi-goal EO-CN-based VANET routing protocols. It's a technique variant in which the fitness function's various criteria are computed simultaneously. This effort aimed to boost performance indicators such as packet delivery rate, routing bandwidth, normalization, and round-trip time.

$$Eff = Gf_k - G * VCE + f_i \quad (3)$$

In the above equation (3), Gf_k be the gravitational force constant, G is the gravity variable, VCE be unity vector to earth's equator and f_i be the intensity of attraction.

All particles change where and how fast they go in the search space at each iteration by updating their pi values. The best-known local position and the particle's current fitness both have a role in determining its trajectory. If the particle's fitness is enhanced, it will use its velocity (local change) to relocate to a more optimal location. That will drastically cut down on the time spent collecting QoS metrics. This approach allows for an iterative search for the optimal particle or leader. The cycle will continue until some predetermined condition is met. Packet delivery success rate and round-trip time are two performance metrics confirmed to be best served by the EO-CN optimization-based computed configuration. There were significant routing overheads associated with the configuration. There is room for more research into this topic, particularly for massive VANETs, where the added computation time associated with a more sophisticated setup might significantly lengthen the end-to-end delay.

$$F_K = (\partial 1 * F1) + (\partial 2 * F2) \quad (4)$$

F_K be the fitness function for k values, $\partial 1$ and $\partial 2$ be the weight factor for each function as shown in equation (4).

The optimal routing strategy for VANETs can be found by finding an overall bi-objective variable that takes residual bandwidth (BW) and final delay (DY) into account. Put simply, the objective of the suggested integrated model is to maximize the differential delay and residual bandwidth between both ends of the connection as much as possible. This allows for the conveyance of data packets along their entire journey from source to destination which is determined to be the most efficient.

$$Delay'(s,d) = Delay(s,d) + \emptyset_{Delay}(T1 + \partial_{Delay} - Delay(s,d)) \quad (5)$$

$$BW'(s,d) = BW(s,d) + \emptyset_{BW}(T2 + \partial_{BW} - BW(s,d)) \quad (6)$$

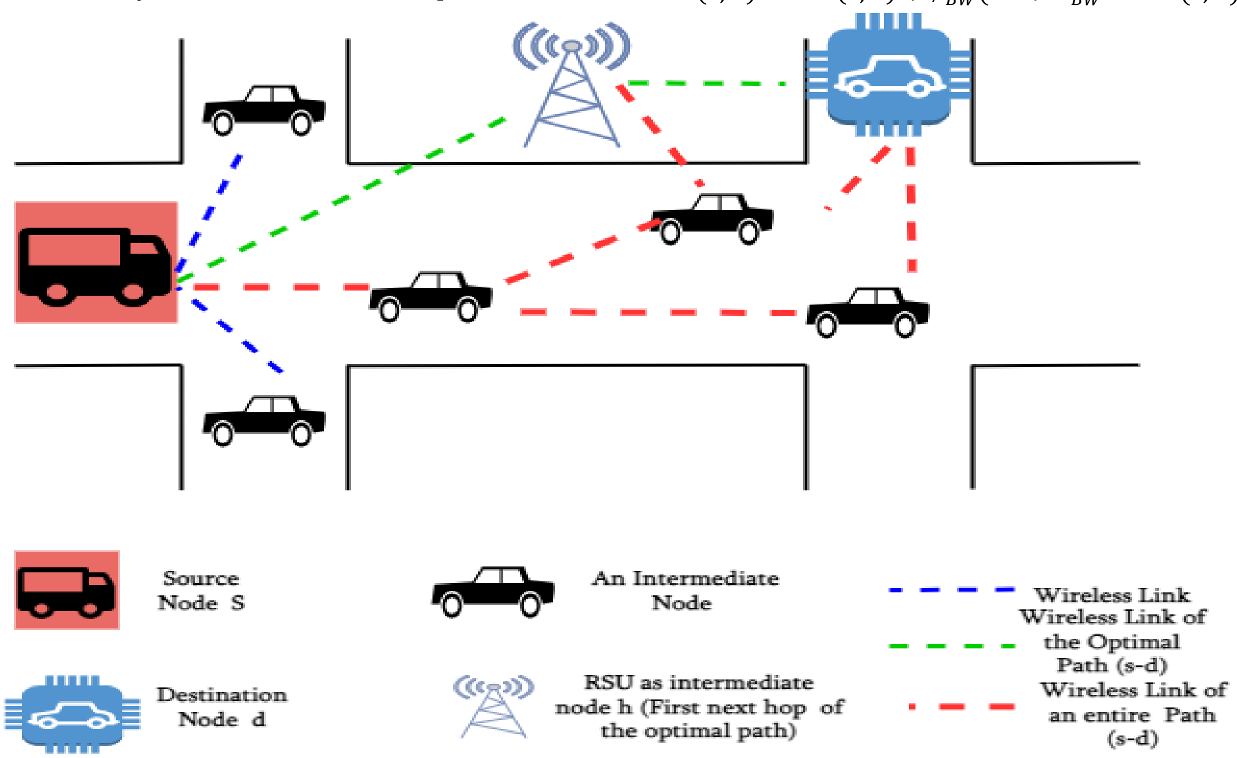

Figure 5 Routing in a Multi-Path VANET

After the next hop has been selected, the above equations Node s can alter its reinforcement functions by adjusting the global goal value for the latency from end to end and end-to-end residual bandwidth, where _Delay and _Delay represents the packet transmission between h and s and the delay learning rate, and _BW and _BW represent the remaining the

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bandwidth between h and s and the amount of bandwidth learning rate, respectively in equations (5) and (6), as shown.

We propose an RL theory that proposes a routing table that will keep track of end-to-end delay values Delay (s, d) and an array of from beginning to end leftover bandwidth values BW (s, d) for every stop d and each immediate next hop h to determine the best path parameters.

$$Delay'(s,d) = Delay(s,d) + \left(1 - \emptyset_{Delay}\right) + \emptyset_{Delay}\,(T1 + \partial_{Delay}) \quad (7)$$

$$BW'(s,d) = BW(s,d) + (1 - \emptyset_{BW}) + \emptyset_{BW}\,(T1 + \partial_{BW}) \quad (8)$$

The above equations (7) and (8) represent the new estimations of delay and bandwidth for the above given functions.

In addition, as illustrated in Figure 5, by communicating with its immediate neighbors, then its extra neighbors, and finally its target, node h is able to determine the remaining path's bandwidth and delay. After receiving the packet at node h, the RIS (s,d) signal is sent to node s along with an estimate of the bi-criteria (Delay and BW) that will let the packet to reach its destination d as fast as feasible using reinforcement learning. The largest residual bandwidth and smallest latency along the shortest link from node h to node d make up the reinforcement signal (s, d).

$$\mathrm{RIS}(s,d) = \begin{Bmatrix} \mathrm{T1} = \min(\sum \mathrm{Delay}(j, \mathrm{nexthop}(j))) \\ \mathrm{T2} = \max(\sum \mathrm{BW}(j, \mathrm{nexthop}(j))) \end{Bmatrix} \quad (9)$$

In the above equation (9), RIS (s, d) is the reinforcement learning signal. $Delay$ is the amount of delayed signal. BW is the bandwidth of the signal. To determine the ideal value for h, a bi-criteria function was utilized, which was discovered utilizing Pareto optimal solutions.

When considering end-to-end latency and end-to-end residual bandwidth, the chosen option gives the best available path, leaving no better possibilities. Therefore, to choose the best h from the non-dominated alternatives, the user favors one criterion, which are the Pareto optimal responses.

Step 1: Get all the cars in their designated lanes

Step 2: Orient the nodes as desired.

Step 3: Adjust the velocities of all vehicles.

Step 4: Construct a Mesh topology

Step 5: Distances between vehicles can be calculated using the network topology and their related nodes.

Step 6: Search space initialization C_{min} and C_{max}

Step 7: For iterations 1 to 8

While (Nodes! - empty)

Node clustering = All node

End While

While 1<= iterations

Step 8: Update C

Step 9: Iteration + 1

Step 10: End While

Step 11: End for

Algorithm 1 Efficient Optimization

The above algorithm 1 shows the initialization steps. A vehicle's direction and speed are decided randomly from the initial point in 2d. The values can be thought of as inputs for a running program. New fitness values are obtained and measured from the search space at each iteration by adjusting the vehicle weights and positions. This algorithm's result will be near-optimal clusters with even distributions of work. It is important that when building clusters, the number of workers assigned to each cluster leader is about the same.

Table 2 Comparison of Different Standards

Number of Nodes	GOA	CAMONET	WOACNET	VANET	QRNGs	CLPSO	EO-CN
10	12.4	35.4	46.7	50.1	55.3	58.2	60.3
20	15.5	24.8	48.5	50.4	59	59.3	62.2
30	19.3	29	45.2	52	63.5	63	64
40	21	32.8	43.9	58.7	67.3	66.1	68.9

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50	29.2	39.1	59	59.9	79.5	74.3	74.4
60	24.4	30.3	41.3	55.1	70.9	72.2	76.6
70	25.8	30.6	48.6	53.5	69.1	69.5	77.9
80	30.1	43.7	55.6	67.4	71	77.9	79.6
90	32.6	41	57.8	63.7	74.3	76.7	80.2
100	30.7	48.6	50.4	69.1	78.9	80.7	81.3

The above table 2 shows the comparison of different standards against the proposed method. To demonstrate the functionality, this research employs EO-CN. The proposed solution significantly decreased network overhead in environments with a wide range of node densities. Experiments were run using varying values of cluster size, network area, node density, and transmission distance, among many others.

4. RESULTS AND DISCUSSIONS

Table 3 shows the numerical results for several configurations that are included in this work. These settings include, yet are not limited to, the following: network size, number of nodes, distance between nodes, and load distribution over nodes. An alternative to taking the long way around to get better data privacy, routing, and security is to implement Efficient Optimization of Vehicular Ad hoc Networks by Clustering Nodes [EO-CN]. The proposed strategy was tested and analyzed using this simulation analysis tool. View the graph below to observe how this section safeguards against other well-known models. Table 4 below shows the simulations parameters (GOA, CAMONET, WOACNET, VANET, and CLPSO).

Table 3 The Data Set

No	Information	Content
1.	Sum of user nodes	10,20,30,40,50,60,70,80
2.	For Clients	10,20, 30…90,100
3.	Total amount of Nodes	85
4.	Instructional Material Samples	88%
5.	Initial Evaluations	80%

Table 4 Simulation Parameters

Method No	Simulation Parameter	Parameter Description
1	GOA	Grasshopper Optimization Algorithm
2	CAMONET	Clustering Algorithm Centered on Moth-Flame Optimization
3	WOACNET	Whale Optimization Algorithm for Clustering in Vehicular Ad Hoc Networks
4	VANET	Vehicular Ad Hoc Networks
5	QRNGs	Quantum Random Number Generators
6	CLPSO	Comprehensive Learning PSO
7	EO-CN	Efficient Optimization of Vehicular Ad Hoc Networks Assisted by A Clustering Nodular

4.1. Cluster Size Analysis

The results are analyzed using the cluster size analysis described above. Figure 6 shows a scatterplot of the proportion of nodes in a cluster relative to their total number. The EO-CN strategy outperforms larger clusters in terms of productivity. Clusters must reach their destination by a specific technique within a specified time window. Compared to other methods, the suggested EO-CN model is far more effective.

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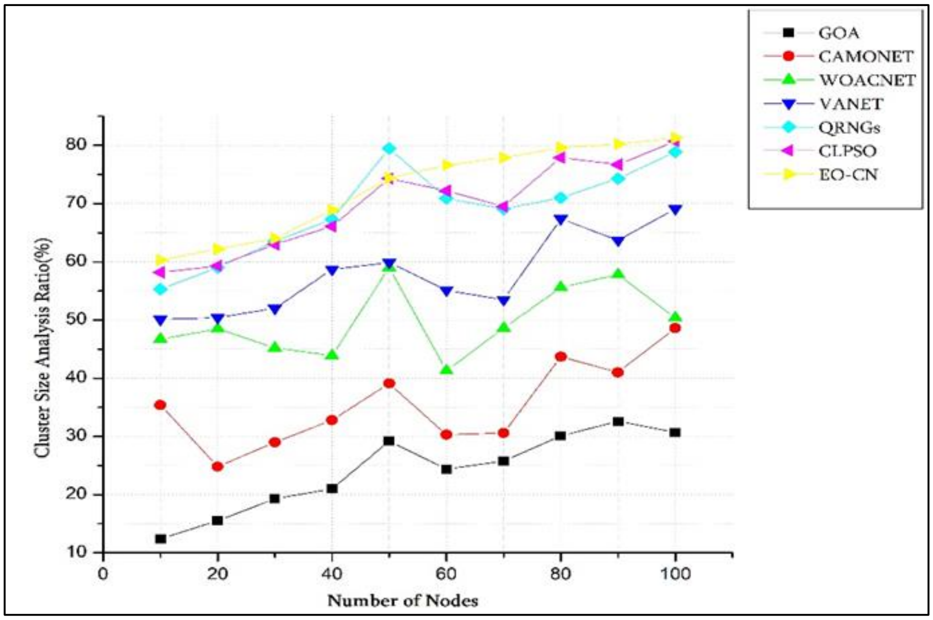

Figure 6 Cluster Size Analysis

4.2. Network Area Analysis

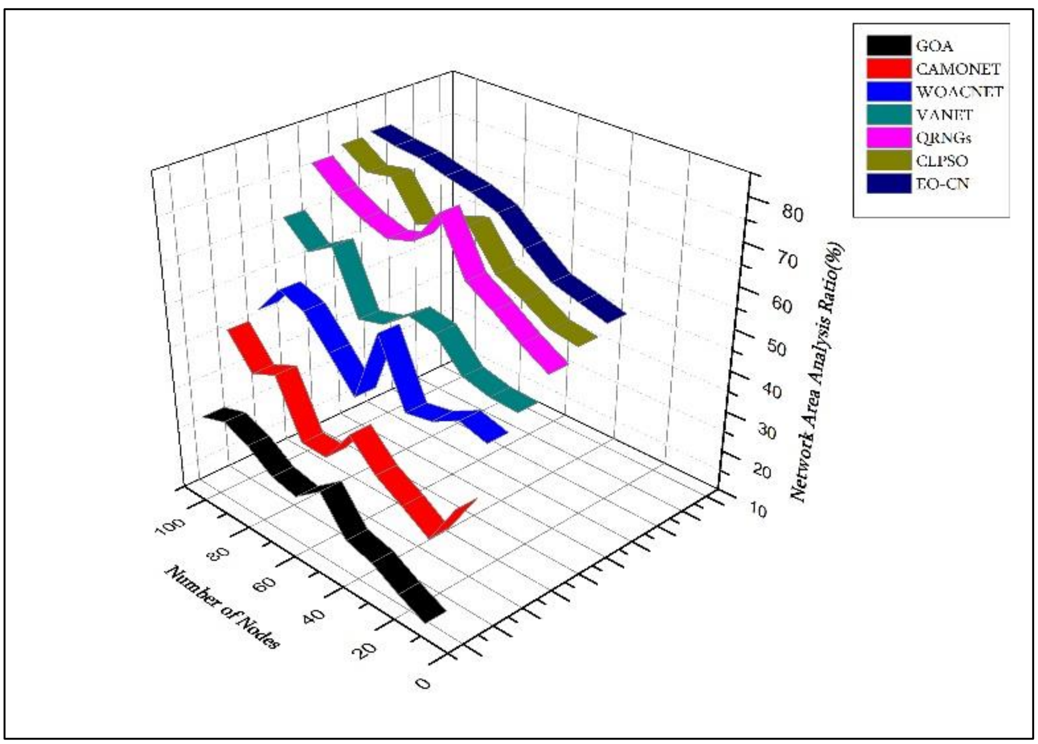

Figure 7 Network Area Analysis

The network above area method examines the findings. Figure 7 shows research of the network's area relative to the overall count of nodes. The EO-CN approach is more productive for growth than a wider network. Within a specified amount of time, a network that uses a particular technique must reach its destination. We found that the proposed EO-CN model significantly outperformed the alternatives.

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4.3. Node Density Analysis

The results are analyzed using the node density technique. Figure 8 depicts research into node density as a percentage of total nodes. The EO-CN strategy is more productive for growth than a wider node density. It is imperative that a node density utilizing a particular method reaches its ultimate destination within a given timeframe. We found that the suggested EO-CN model outperformed the others by a significant margin.

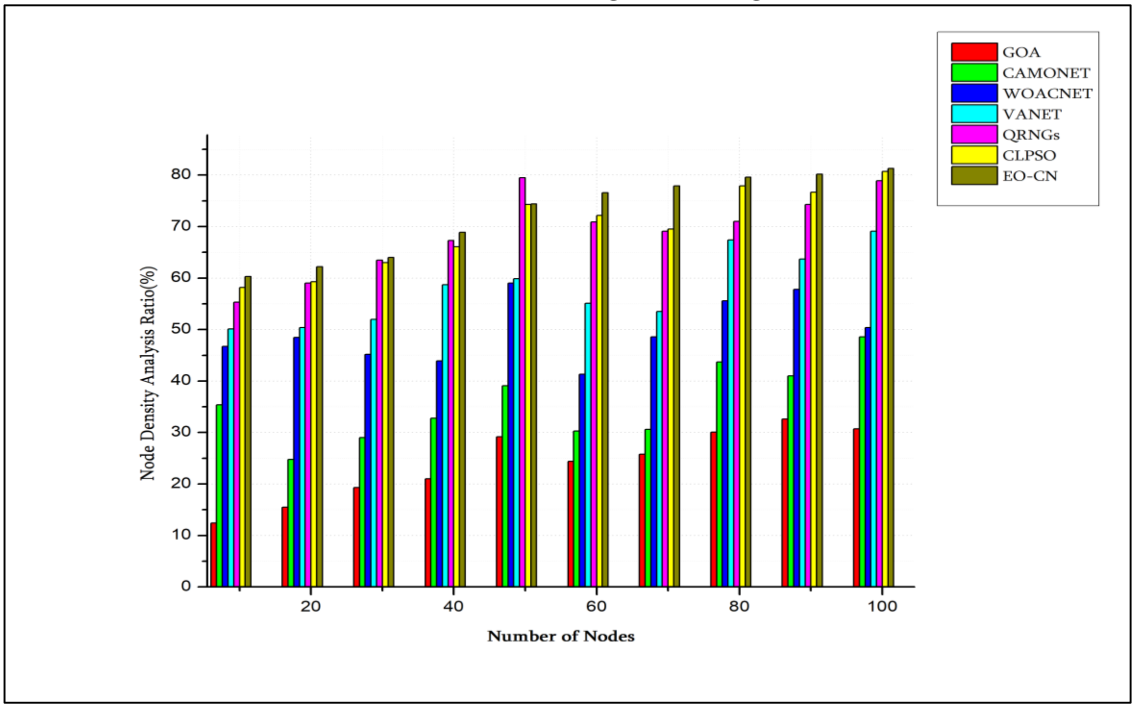

Figure 8 Node Density Analysis

4.4. Transmission Distance Analysis

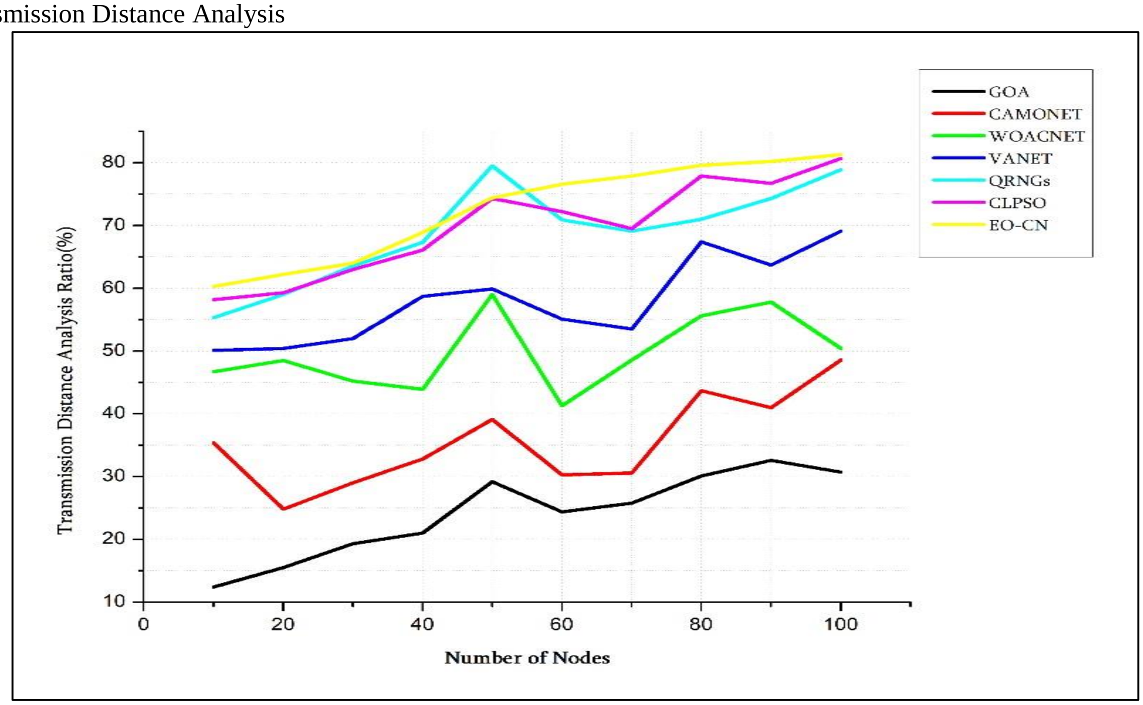

Figure 9 Transmission Distance Analysis

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The results are examined with the use of the Transmission Distance method. Transmission-distance studies as a share of total nodes of interest are shown in Figure 9. Compared to increasing the Transmission Distance, the EO-CN technique is more beneficial to growth. Following a given strategy, a node density must arrive at its target in a predetermined time. We found that the proposed EO-CN model significantly outperformed the alternatives.

4.5. Efficiency Analysis

The effectiveness technique is applied to the obtained data, and efficiency as a share of total nodes of interest is displayed in Figure 10. The EO-CN method is more productive for expansion than simply boosting efficiency. The goal density of a network must be reached within a certain amount of time using a specific technique. The proposed EO-CN model performed noticeably better than the other options we considered.

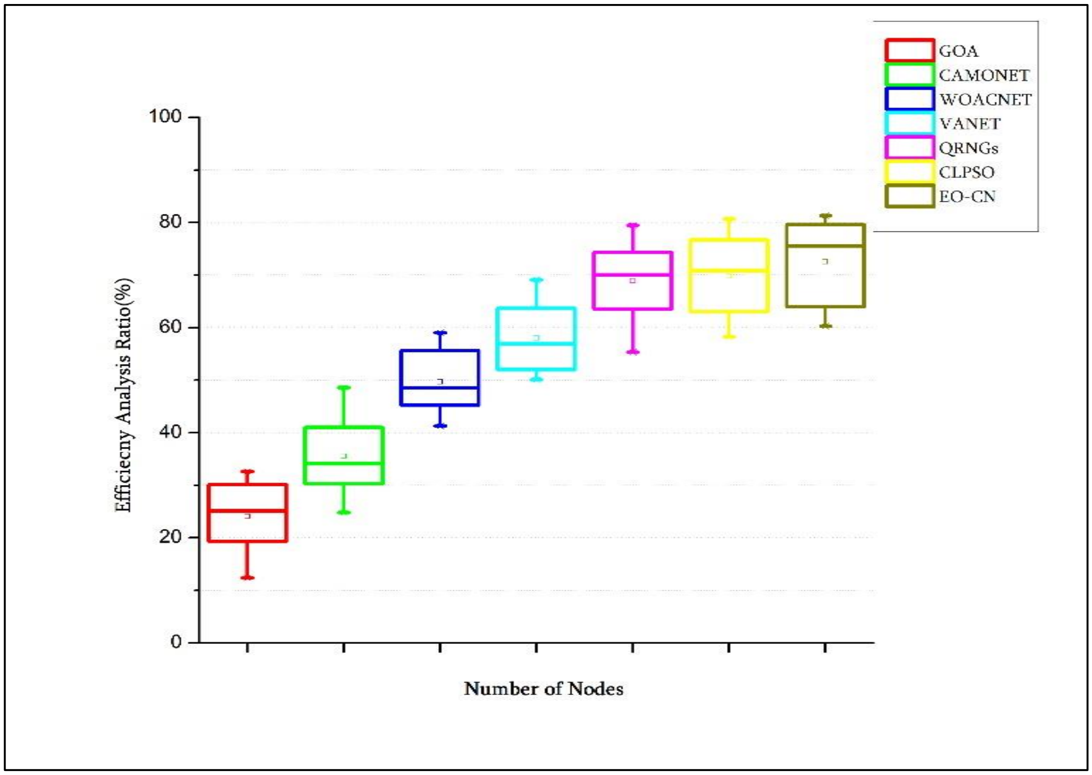

Figure 10 Efficiency Analysis

5. CONCLUSION

For VANETs, we have classified evolutionary algorithms and other bio-inspired techniques into three distinct groups. Some of the most crucial sending and computational criteria that have been used to classify, evaluate, and compare research studies within each category include difficulty, flexibility, durability, accessibility model employed, and the level of Quality of Service (QoS) the efficiency of the routing process (latency, ratio of packet transmission, routing overhead, and via input). Our proposed unified formal model is built on a reinforcement learning system and may be used to evaluate the convergence of VANET routing. The model's global objective function stands for the performance requirements of route discovery, maintenance, optimization, etc., and seeks multiple solutions. The suggested model is better suited for bio-inspired approaches than conventional exact methods, in which the emphasis is placed on online performance with no suboptimal actions explicitly offered for reinforcement learning. It cannot be easy to efficiently share data in VANETs due to variations in node density and traffic loads. Hence, a clustering strategy was presented in this research to improve communication in environments with medium and high node densities. The developed algorithms have produced multiple solutions, improving the users' efficiency. Having fewer clusters in the network reduces the overall cost of packet routing. Because of these algorithms' evolutionary capabilities, we can search a broader space and make real-time changes to the values of our objective functions. The results of the trials are used to demonstrate the algorithms' scalability and effectiveness. Effective Optimization of

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Vehicular Ad hoc Networks by Node Clustering [EO-CN] is offered to address the problems above. The proposed technique significantly decreased network overhead in environments with a wide range of node densities.

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