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Original Article

Efficient Clustering and Routing using Multi-Objective Dynamic Osprey Optimization Algorithm in Vehicular Ad-hoc Network

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Abstract - *Vehicular Ad Hoc Network (VANET) is a developing technology applied in Intelligent Transportation Systems. The existing research has limitations, such as network instability due to vehicles' mobile nature, which reduces the network lifetime. To overcome this problem, this research introduced a Multi-objective Dynamic Osprey Optimization Algorithm (MDOOA) based on energy-efficient clustering and routing in VANET. In the exploration phase, a dynamic, elite guidance mechanism with an adjustable ratio strategy is used to enhance individuals' search space exploration and avoid local optima issues at the beginning of the iteration. The MDOOA is used for Cluster Head (CH) and route selection with objective functions like the distance between neighbor nodes, the distance between Base Station (BS) to CH, energy, centrality and Load Balancing Factor (LBF), which gradually contributes to enhancing Network Lifetime (NLT). The CH maintenance is also performed using MDOOA to balance loads among clusters, which is required to prevent node failure. The delay, Packet Delivery Ratio (PDR), NLT, Energy Consumption (EC) and throughput are considered for experimental analysis of MDOOA. The experimental results show improvement in delay, Packet Delivery Ratio (PDR), NLT, Energy Consumption (EC) and throughput when compared with the existing techniques.*

Keywords - *Cluster head maintenance, Dynamic, Elite guidance mechanism, Load Balancing Factor, Osprey Optimization Algorithm, Vehicular Ad Hoc Network.*

1. Introduction

The Vehicular Ad hoc Network (VANET) is one of the distinct categories of Mobile Ad hoc Networks (MANETs) in that vehicles are taken as nodes, and complete transmission commonly occurs among them [1]. The data is communicated by Vehicle-to-Infrastructure (V2I), Vehicle-to-Everything (V2X) and Vehicle-to-Vehicle (V2V) communications [2]. VANET is applied in different areas, such as monitoring traffic congestion, safety driver programs and traffic control [3]. In VANET, data is transmitted without infrastructure, and communication is comprehensive due to the promoting mechanism over a few hops [4]. The clustering denotes the procedure of partitioning the whole set of vehicle nodes into small logical groups within a network [5]. The clustering is based on various parameters like transmission capability and inter-node distance for optimizing overall network performance [6, 7]. However, the clustering processes deviate from each other based on various criteria considered for forming clusters related to their application functionality and domain [8].

Particularly, CH is responsible for forwarding intra-cluster and inter-cluster communication while Cluster Member (CM) nodes act as actual nodes [9-11]. The CH selection is related to its improved functionality, attributed to the network optimization performance [12]. Therefore, the CH selection in VANET plays a significant role in obtaining reliable communication [13]. However, VANET has limitations, such as dynamic behavior rectified through efficient and effective routing for data broadcasts [14, 15]. Vehicles cannot communicate data without an effective routing technique and will lose every benefit of sophisticated VANET technology [16]. Important services allowed through VANET are hazard control systems and handling services, which require data management towards certain subsets or nodes in the network to enable required action. One main issue with data distribution is its implied risk of broadcast or bottleneck storms [17-20]. In VANET, managing stable and long-lasting network connections is difficult because of the vehicle's high mobility, which minimizes the overall network lifetime and efficiency in data transmission. The MDOOA is proposed for energy-efficient clustering and routing in VANET to solve this research gap. MDOOA addresses the instability in VANET by generating more robust clustering and routing mechanisms that adjust to the high mobility of vehicles. The dynamic, elite guidance mechanism with an adjustable ratio strategy is deployed to manage clusters towards optimal routes by determining energy-efficient nodes effectively. In the exploration phase, the adjustable ratio strategy adapts the search space in the early iteration phase to avoid local optima issues. By continuously refining the search, the MDOOA minimize energy consumption, increases the overall network lifetime, stabilizes the network connectivity, and enhances data transmission. The vital contributions of this manuscript are as follows.

- The MDOOA is used for CH selection with the help of objective functions like the distance between neighbor nodes, the distance between BS to CH, energy, centrality and Load Balancing Factor (LBF). Moreover, route selection is performed through objective functions like distance between BS to CH and energy, which progressively contributes to enhancing network lifetime.
- The MDOOA finds different routes and optimizes the best route for reducing energy consumption and delay, enhancing the overall network lifetime. Additionally, the CH maintenance is performed using MDOOA to balance loads among clusters, which is required to prevent node failure.

The rest portion of this research is prepared as subsequent: Section 2 summarizes existing research; Section 3 details the proposed methodology. Section 4 gives implementation results, and Section 5 concludes the research.

2. Literature Review

Effective clustering and routing in VANET were significant in optimising vehicle communication and increasing road safety and traffic management. Clustering contains grouping vehicles depending on mobility patterns to effectively exchange data and enhance scalability. The routing mechanism adapts to the dynamic nature of vehicle movement, providing high reliability and low latency. Various algorithms have been developed for CH and route path selection to enhance network lifetime in VANET. The methodology, advantages and limitations are examined below:

Raghu Ramamoorthy and Menakadevi Thangavelu et al. [21] presented an Enhanced Hybrid Ant Colony Optimization Routing Protocol (EHACORP) for clustering and routing in VANET. Initially, the EHACORP depends on distance estimation techniques to calculate distance among vehicles. The source-based ACO was utilized to create a shorter path with fewer hops to communicate data. The EHACORP was applied to achieve better balance within the network. The objective functions considered are based on distance and energy and do not consider centrality and LBF, which affect energy efficiency. From the overall evaluation of [21] enhances network balance by optimizing routing depending on energy and distance, but lack of consideration for LBF and centrality limits its energy efficiency.

Mohamed Elhoseny et al. [22] developed an Intelligent Energy-Aware Oppositional Chaos Game Optimization-based Clustering (IEAOCGO-C) protocol for VANETs. This technique aims to select Cluster Heads (CHs) in the network efficiently and construct clusters based on Oppositional-Based Learning (OBL) with Chaos Game Optimization (CGO) algorithm to improve efficiency. The combination of CGO and OBL leads to faster convergence rates due to the efficient search mechanism of CGO and the comprehensive solution space evaluation of OBL. However, the IEAOCGO-C approach has increased sensitivity to parameter settings, requiring more extensive tuning to achieve optimal performance. In the overall analysis of [22], convergence rates increased through solution space exploration but exhibited enhanced sensitivity, leading to inaccurate performance.

S. Harihara Gopalan et al. [23] implemented a Data Dissemination Protocol (DDP) for VANET routing protocols. Multiple routes were found using a Time Delay-based Multipath Routing (TD-MR) approach, transmitting messages to the destination node and Particle Swarm Optimization (PSO) was utilized to find the optimal and secure path. This approach efficiently performed in finding a secure routing path, demonstrating strong search capabilities due to its collective behavior and information-sharing mechanisms, which allow it to explore the solution space efficiently. It converges to an optimal solution within the constraints of the network routing issue, particularly in highly dynamic environments. However, when performing route selection, it communicated huge control packets that led to a high routing load. From the overall determination of [23], the approach effectively converges to the optimal solution but suffers from routing load during route selection, which affects the overall network effectiveness.

T. S. Balaji et al. [24] developed a T2FSC-MOR for VANET. The T2FSC technique utilized various parameters such as Link Quality (LQ), Inter-Vehicle Distance (IVD), Traveling Speed (TS), Neighboring Node Count (NNC) and Trust Factor (TF). Additionally, Trust Aware Seagull Optimization-based Routing (TASGOR) was applied to optimize route selection in VANET. To validate the T2FSC-MOR, a simulation set was considered and examined using various metrics. The T2FSC-MOR has less delay and communication cost because of the selection of the best routes. However, it does not perform cluster maintenance for balancing loads among clusters, which leads to node failure. In the overall analysis of [24], it minimize costs and delays, but it lacks maintenance to balance loads among clusters. Mumtaz Ali Shah et al. [25] implemented an Optimal Path Routing Protocol (OPRP) for CH and route selection in

VANET. The OPRP depended on mobility measures for cluster formation to avoid communication overhead in a huge mobility environment. Additionally, communication among CH was used to minimize transmission numbers, and CH was selected through a median approach relying on even or odd vehicle numbers for stable clusters. This protocol reduces node failure and net dysconnectivity in routing. However, it does not consider distance in the route path, which consumes high energy if the route has a high distance. From the overall evaluation of [25], there is a decrease in node failures and network disconnections, but a lack of consideration of distance results in high energy consumption, which minimizes overall effectiveness.

Based on the above analysis, the centrality and LBF are not considered, affecting energy efficiency. The model interconnected huge control packets when performing route selection, which leads to a high routing load. Cluster maintenance is not performed to balance loads among clusters, which leads to node failure. The distance is not considered in the route path, which consumes high energy because the route has a large distance. In this research, MDOOA-based clustering and routing are proposed to enhance NLT in VANET. The objective functions, which are the distance between neighbor nodes, the distance between BS to CH, energy, centrality, and LBF, are considered for clustering and routing, which enhances NLT and reduces EC and delay.

3. Proposed Methodology

In MDOOA, CHs and routes are selected to achieve energy-efficient, reliable data transmission for VANET. Initially, nodes are randomly initialized, and CHs are selected from vehicle nodes using the distance between neighbor nodes, the distance between BS to CH, energy, centrality and LBF. Then, clusters are formed based on potential functions such as energy and distance. The route selection is presented by MDOOA using the distance between BS to CH and energy. Then, CH maintenance is presented through MDOOA to balance the load among clusters. Figure 1 presents the block diagram of MDOOA.

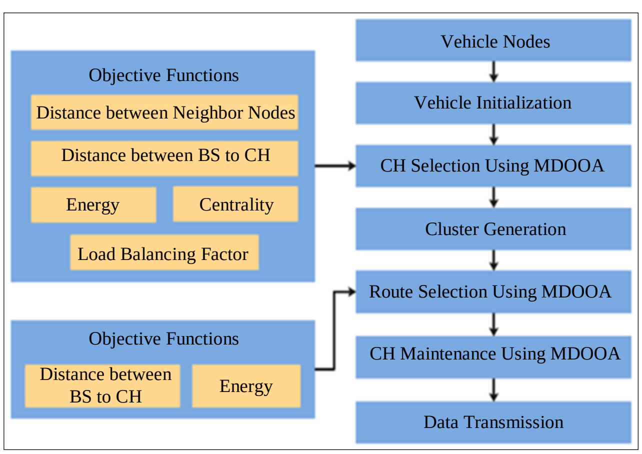

Fig. 1 Block diagram of MDOOA in VANET

3.1. Node Deployment

Initially, nodes are deployed randomly in the area of VANET and then energy-efficient-based CHs and routes are selected using MDOOA, which helps to obtain reliable data transmission in VANET.

3.2. Node Initialization

The primary solution for the ospreys is fixed through a set of candidate nodes. The random node ID from 1 to S is used to initialize the osprey's solution where S indicates every node in VANET. Consider osprey i as $X_i = (X_{i,1}, X_{i,2}, \dots, X_{i,d})$ Where d is a dimension of MDOOA, equivalent to the number of CHs.

3.3. CH Selection Using MDOOA

The OOA is a population-based intelligent optimization algorithm stimulated through the hunting behavior of osprey in nature. Like other intelligent optimization algorithms, it performs random population initialization in search space as Equation (1),

$$x_{i,j} = lb_j + r \cdot (ub_j - lb_j) \tag{1}$$

Where the individual population is $x_{i,j}$, the lower and upper bound of search space is lb_j and ub_j, a random number in [0, 1] is signified as r. The primary phase of OOA is the exploration phase, which is demonstrated by simulating its position and fish-catching behavior in nature. At the OOA design process, all population individuals are examined other individuals through better positions as school fish and target schools for all individuals are mathematically indicated as Equation (2),

$$FP_i = \{X_k | k \in \{1,2, \dots, N\} \wedge F_k < F_i\} \cup \{X_{best}\} \tag{2}$$

Where the set of fish for eagle i is indicated as FP_i and the position of the best eagle is X_{best}. In this exploration phase, a dynamic, elite guidance mechanism with an adjustable ratio strategy is used to enhance individuals' search space exploration and avoid local optima issues at the start of the iteration. However, the targets are selected randomly through individuals under a random search strategy. As the number of iterations increases, the random search strategy enhances the invalid searches through this algorithm. The dynamic strategy is applied in the exploration phase, and its individual position update is as shown in Equation (3),

$$x_{i,j}^{NEW} = x_{i,j} + \alpha \cdot r_{i,j} \cdot (X_{i,j}^{best} - X_{i,j}) + (1 - \alpha) \cdot r_{i,j} \cdot (SF_{i,j} - I_{i,j} \cdot x_{i,j}), \alpha = \frac{t}{T} \tag{3}$$

Where individual population positions with optimal fitness value are signified as $X_{i,j}^{best}$, the dynamic adjustment factor is α, which is used to manage the ratio among elite bootstrapping mechanisms and randomized exploration. The

α linearly progresses from 0 to 1 with each iteration. The dynamic factor, the MDOOA, shifts individual position updates from random exploration to elite guidance at the exploration stage as increased iterations.

During the start of the iteration, the lesser score of α enables the focus on exploration to enhance randomness to explore solution space and avoid local optima issues. If iteration increases, the α values are enhanced, and individual position update concentrates on elite guidance, which covers local optima solutions and reduces invalid searches. The boundary checking is implemented for individuals with entire position updates with Equation (4),

$$x_{i,j}^{NEW} = \begin{cases} x_{i,j}^{NEW}, & lb_j \leq x_{i,j}^{NEW} \leq ub_j \\ lb_j, & x_{i,j}^{NEW} < lb_j \\ ub_j, & x_{i,j}^{NEW} > ub_j \end{cases} \tag{4}$$

If the individual position update is enhanced over the earlier position, which is exchanged through the new position as Equation (5),

$$X_i = \begin{cases} x_i^{NEW}, & F_i^{NEW} < F_i \\ X_i, & else \end{cases} \tag{5}$$

Where updated position and its fitness value are signified as x_i^{NEW} and F_i^{NEW}. After capturing a fish in the wild, the osprey acquires a fish in a safer position to feed.

Based on this behavior, the development phase of the algorithm is displayed. Every population individual estimates random new positions as feeding areas, and its behavior is signified in Equation (6),

$$x_{i,j}^{NEW_2} = x_{i,j} + \frac{lb_j + r\cdot(ub_j - lb_j)}{t} \tag{6}$$

Boundary checking of every individual through the position update phase as Equation (7),

$$x_{i,j}^{NEW_2} = \begin{cases} x_{i,j}^{NEW_2}, & lb_j \leq x_{i,j}^{NEW_2} \leq ub_j \\ lb_j, & x_{i,j}^{NEW_2} < lb_j \\ ub_j, & x_{i,j}^{NEW_2} > ub_j \end{cases} \tag{7}$$

The new position is applied to exchange the actual position. If the new position is better, compare the updated with actual individual position quality as in Equation (8),

$$X_i = \begin{cases} x_i^{NEW_2}, & F_i^{NEW_2} < F_i \\ X_i, & else \end{cases} \tag{8}$$

Where updated individual position and fitness value are signified as $x_i^{NEW_2}$ and $F_i^{NEW_2}$.

3.4. Objective Functions

The objective functions, such as the distance between BS to CH and the distance between neighbor nodes, centrality, LBF, and energy, are considered to find the optimal CH using MDOOA, which are explained below.

3.4.1. Distance between Neighbor Nodes

It denotes the ranges among actual neighbor nodes and their CH. The energy depletion for nodes is based on communication path distance. If the selected node has less communication distance near BS, the energy consumption of the node is small. Distance between neighbor nodes (f_1) is defined in Equation (9),

$$f_1 = \sum_{j=1}^{m} \sum_{i=1}^{I_j} D(s_i, CH_j / I_j) \tag{9}$$

Where, $D(s_i, CH_j/I_j)$ is a ith sensor, and CH_j, I_j is sensor node quantity among CH.

3.4.2. Distance between BS and CH

The node's energy consumption is calculated through distance over the communication track. When BS is positioned far from CH, data transmission needs huge energy. As a result, the rapid drop in CH is associated with enhanced energy usage. Hence, the node near to BS is selected throughout the data transmission. The distance between BS and CH (f_2) is defined in Equation (10),

$$f_2 = \sum_{i=1}^{m} D(CH_j, BS) \tag{10}$$

Where, $D(CH_j, BS)$ is the distance among BS and CH_j.

3.4.3. Energy

The CH gathered data from nodes and communicated it with BS in the network. Because the CH consumes huge energy to accomplish earlier activities, the node with high energy is the best choice for CH. The optimal solution of energy (f_3) is defined in Equation (11),

$$f_3 = \sum_{i=1}^{m} \frac{1}{E_{CHi}} \tag{11}$$

Where, E_{CHi} is a ith CH's energy.

3.4.4. Centrality

Higher centrality in the network efficiently reduces the communication distance among CM, enhances energy efficiency, and reduces delay and overall network performance. Node centrality (f_4) is a measure that indicates the relative distance of the node from its neighbors as Equation (12),

$$f_4 = \sum_{i=1}^{m} \frac{\sqrt{\frac{\left(\sum_{j\in n}^{m} D^2(i,j)\right)}{n(i)}}}{L} \tag{12}$$

Where $n(i)$ is a number of CH's neighbor nodes, L is a network dimension.

3.4.5. Load Balancing Factor

The LBF is integrated as an assessment tool associated with any technique to measure the load of CH. Every CH deals with its equivalent number of cluster nodes; however, maintaining balanced loads among systems is difficult. The basic explanation is the consecutive connection and separation of neighbors from CHs. The cluster size elements show CH loads and LBF (f_5) is defined in Equation (13),

$$f_5 = \frac{1}{nCH \times \sum (xi - \mu)^2} \tag{13}$$

Where nCH is a number of CH, xi is a ith cluster node, μ is an average load for all CH.

All the objective functions do not strongly conflict with each other in nature; hence, instead of optimizing them individually, the weighted-sum approach is used for all objective functions to convert into a single objective function as Equation (14),

$$Fitness = \alpha_1(f_1) + \alpha_2(f_2) + \alpha_3(f_3) + \alpha_4(f_4) + \alpha_5(f_5) \tag{14}$$

Where, $\sum_{i=1}^{5} \alpha_i = 1$; and $\alpha_i \in (0,1)$, the values of α_i are 0.27, 0.25, 0.23, 0.13 and 0.12 respectively. The $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ and α_5 are weights assigned to every objective functions. In multi-objective optimization, multiple objectives are optimized simultaneously using min-max normalization. Normalizing the values of each objective helps to balance and ensure that one objective does not excessively affect the optimization process. All objectives have different values; thus, min-max normalization is employed for every objective using Equation (15),

$$F(x) = \frac{f_i - f_{min}}{f_{max} - f_{min}} \tag{15}$$

Where, f_i is a value of function, f_{min} and f_{max} are minimum and maximum value, $F(x)$ is a normalized value among 0 and 1.

3.5. Cluster Generation

Here, the selected CHs by MDOOA are given to nodes. In some existing research, clusters are generated, so the possibility of CHs is limited to each cluster. If the selected CHs are inappropriate, it leads to high communication overhead and reduces the network lifetime. By selecting the appropriate CH in this research, the network ensures that CH is capable of handling additional load. This procedure minimizes the communication overhead and enhances the network lifetime. Normally, nodes are allocated to suitable clusters after selecting the CH using MDOOA. Based on the potential function, energy and distance are measured for cluster generation as Equation (16),

$$Potential\ Function\ (S_i) = \frac{E_{CH}}{dis(S_i, CH)} \tag{16}$$

Where, E_{CH} is a CH residual energy and $dis(S_i, CH)$ is the distance among the sensor and CH. The distance between two different CHs and nodes is equivalent, and the node is integrated into CHs with high energy.

3.6. Route Selection

The MDOOA-based energy-efficient route path is implemented in the same way as CH's selection; the formation of routes is processed at different communication levels. The MDOOA is performed effectively for both CHs and route selection, which enhances the network performance. The MDOOA ensures optimal CH selection and cluster generation through enhancing network lifetime and reducing energy consumption. The MDOOA selects the route using the distance between BS to CH and energy parameters. In route selection, the dimension of each population is the same as the number of nodes. The route selection using MDOOA is provided below:

- Primarily, the solution of ospreys is fixed with possible paths from the transmitter BS to CH, where the dimensions are equivalent to the number of transmitted CHs along the route.
- The position update process for possible paths is initialized in each position of the ospreys, equivalent to the iterative process explained in the above section. The fitness considered in the MDOOA to define the route as Equation (17),

$$f = \mu_1 \times \sum_{i=1}^{m} D(CH_j, BS) + \mu_2 \times \sum_{i=1}^{m} \frac{1}{E_{CHi}} \tag{17}$$

Where, $\sum_{i=1}^{2} \mu_i = 1$; and $\mu_i \in (0,1)$, the values of μ_i are 0.4 and 0.6, respectively. The μ_1 and μ_2 are weights assigned to every route objective functions. From this process, optimized nodes are selected to produce routes from nodes to BS. After producing a route from source to destination, the nodes transfer the data to the destination. The shortest distance leads to less communication delay and helps to enhance network lifetime. Energy-efficient route paths are used to enhance network reliability and lifetime. By preserving energy, nodes maintain stable communication for a long time, which reduces node failure and enhances the network lifetime. Therefore, secure route paths are selected, and CH maintenance is explained in the following section.

3.7. CH Maintenance

The CH maintenance is one of the main stages in this research for balancing load among clusters. The maintenance of the cluster is required to prevent node failure. The MDOOA is reset to the network cluster if the energy of CH exceeds the threshold level. Then, the CH is selected through MDOOA with the help of five objective functions: the distance between BS and CH, the distance between neighbor nodes, centrality, LBF, and energy. These objective functions are applied to select optima CH among nodes. The BS continuously monitors the energy of nodes to avoid node failure at data transmission. From source to BS through CH, the MDOOA is applied to find the best data transmission route path with the help of the distance between BS to CH and energy. It finds the best path to reduce energy consumption and enhance the network lifetime. This MDOOA-based clustering and route path selection results in an energy-efficient data transmission in VANET. During data transmission, an energy-efficient VANET is applied to enhance the entire transferred packets to BS thereby enhancing the network lifetime.

4. Experimental Result

The MDOOA is implemented using MATLAB R2018a with a system configuration operating system of Windows 10 Ultimate, random-access memory of 16GB and Intel (R) Core (TM) i5-3570 CPU @ 3.40GHz processor with the 64-bit operating system. As per the existing method scenarios, we have considered parameters like target area, simulation time, packet size, number of vehicles, initial energy, and mobility model to evaluate the reliability and validity of results. The 10-60 vehicle nodes are distributed randomly in the target area of 2500×2500m. The simulation parameters used for this implementation are listed in Table 1. The main goal of this research is to reduce the usage of entire energy and enhance the network lifetime. As a result, MDOOA-based CHs and route selection are performed to provide energy-efficient cluster-based routing in VANET. For the best CH selection, the distance between BS and CH, as well as the distance between neighbor nodes, centrality, LBF, and energy, are inputs provided to MDOOA. Energy and distance between BS and CH are provided as input to MDOOA for better route selection. The metrics such as delay, PDR, NLT, EC and throughput for calculating MDOOA performance are mathematically expressed in Equations (18)-(22). Lower delay is significant for transmitting the data in a timely manner in VANET. Higher PDR ensures more reliable communication, which directly impacts the data-sharing effectiveness among vehicles. A longer NLT supports sustainable connectivity, which reduces frequent reconfiguration and manages network stability. A minimized energy consumption prolongs the operation of the node, which is essential for effective resource utilization in VANET. Higher throughput supports the effective exchange of data, which increases overall network performance.

$$Delay = \sum(Arrival\ time\ of\ packet - Start\ time\ of\ packet) \quad (18)$$

$$PDR = \left[\frac{\sum_{i=1}^{n} packets\ delivered}{\sum_{i=1}^{n} packets\ transmitted}\right] \quad (19)$$

$$NLT = \frac{\sigma_0 - E_{estimate}[E_{RE}]}{CP + \#E[E_{CE}]} \quad (20)$$

$$EC = (E_{rx} \times numberofnodes) + E_{tx} \quad (21)$$

$$Throughput = \frac{number\ of\ delivered\ packets \times packet\ size \times 8}{Total\ simulation\ time} \quad (22)$$

Where, σ_0 is total energy, CP is an endless power consumption in the network, $E_{estimate}[E_{RE}]$ is an approximate remaining energy, $E[E_{CE}]$ is a consumed energy, E_{tx} and E_{rx} are the total number of transferred and received energy.

Table 1. Simulation parameters

Parameter	Value
Target area	2500×2500m
Simulation time	300s
Initial energy	1mJ
Packet size	4000bits
Mobility model	Random
Number of vehicle nodes	10, 20, 30, 40 and 50

4.1. Performance Analysis

Primarily, MDOOA is analyzed through Distributed Energy-Efficient Clustering (DEEC), Low-Energy Adaptive Clustering Hierarchy (LEACH), Threshold DEEC (TDEEC), Developed DEEC (DDEEC) and Centralized LEACH (CLEACH) since these approaches are implemented using the parameters listed in Table 1. The number of vehicle nodes affects CHs and route selection over VANET. The VANET, with huge nodes, delivers alternative routes for data broadcasting, which enhances reliability. Additionally, VANET with high nodes has evenly distributed energy usage, which minimizes energy consumption. However, the above-mentioned impacts of different nodes are examined through delay, PDR, NLT, EC and throughput, as shown in Figures 2 to 6, respectively.

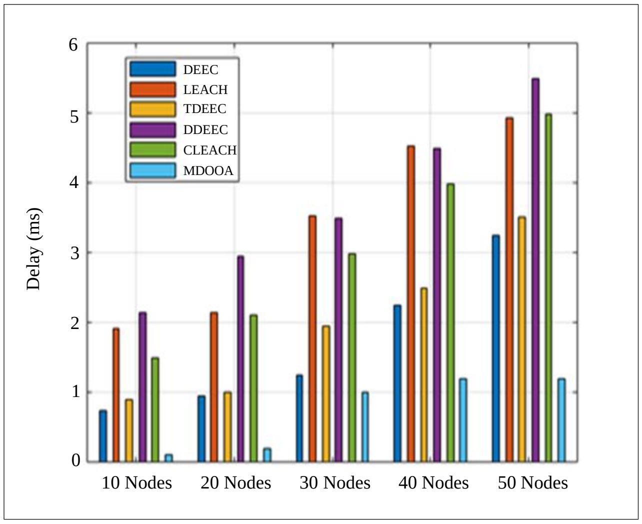

Fig. 2 Delay evaluation with various vehicle nodes

In Figure 2, the delay evaluation of MDOOA is compared with various state-of-the-art methods such as DEEC, LEACH, TDEEC, DDEEC, and CLEACH. The MDOOA achieved less delay of 0.12ms, 0.20ms, 1.00ms, 1.20ms and 1.20ms for different vehicle nodes from 10-50. By taking distance as the objective function, it examined less transmission distance for transmitting data, which reduces the delay. The MDOOA demonstrates efficient performance in CH and routes through achieving less delay.

In Figure 3, the PDR evaluation of MDOOA is compared with various state-of-the-art methods such as DEEC, LEACH, TDEEC, DDEEC, and CLEACH. The MDOOA achieved high PDR of 98.54%, 98.64%, 99.12%, 99.42% and 99.42% for different vehicle nodes from 10-50. Using LBF as an objective function provides a reliable and stable network, enhancing PDR performance. The MDOOA demonstrates efficient performance in CH and routes through achieving high PDR.

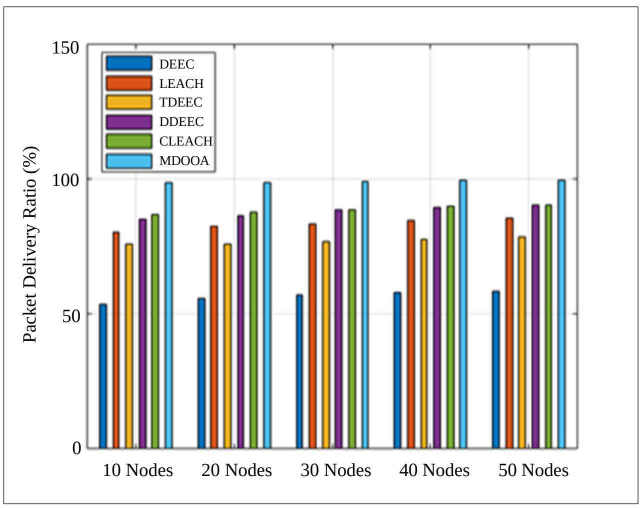

Fig. 3 PDR evaluation with various vehicle nodes

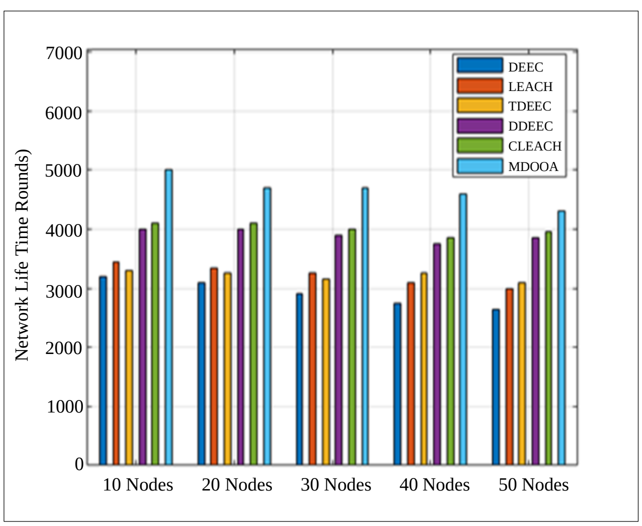

Fig. 4 NLT evaluation with various vehicle nodes

In Figure 4, the NLT evaluation of MDOOA is compared with various state-of-art methods such as DEEC, LEACH, TDEEC, DDEEC, and CLEACH. The MDOOA achieved high NLT of 5000 rounds, 4700 rounds, 4700 rounds, 4600 rounds and 4300 rounds for different vehicle nodes from 10-50. By considering distance as the objective function, the MDOOA achieves less delay, thereby enhancing NLT. The MDOOA demonstrates efficient performance in CH and routes through achieving high NLT.

In Figure 5, the EC evaluation of MDOOA is compared with various state-of-the-art methods such as DEEC, LEACH, TDEEC, DDEEC, and CLEACH. The MDOOA achieved less EC of 20mJ, 24mJ, 26mJ, 30mJ and 32mJ for different vehicle nodes from 10-50. Selecting CH-based energy assists in the distribution of energy consumption, which reduces EC performance. The MDOOA demonstrates efficient performance in CH and routes through achieving less EC.

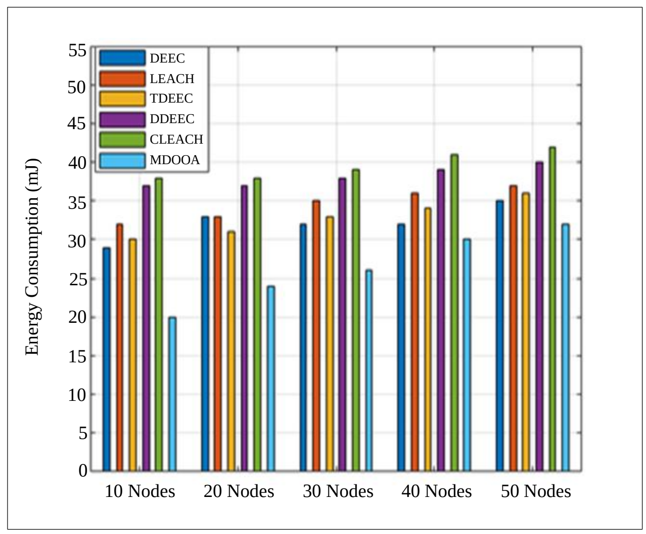

Fig. 5 EC evaluation with various vehicle nodes

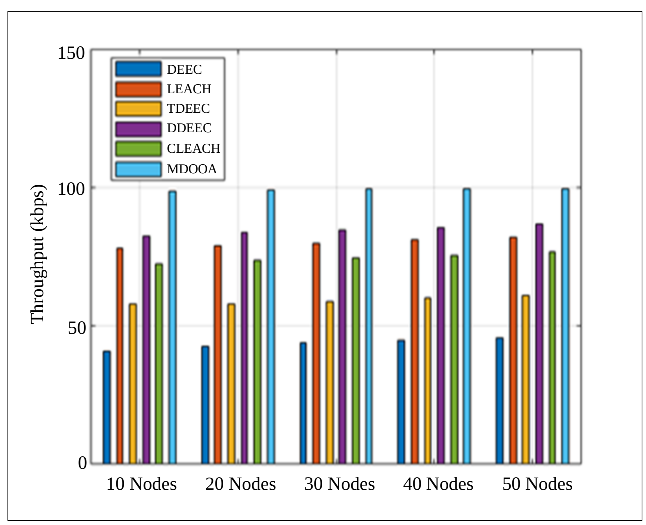

Fig. 6 Throughput evaluation with various vehicle nodes

Table 2. Throughput analysis (kbps) with different optimization methods

Optimization Methods	No. of. Vehicle Nodes				
	10	20	30	40	50
PSO	78	82	85	88	92
MOA	82	84	87	88	90
OOA	92	95	96	97	98
MDOOA	96	97	98	100	100

Table 3. EC analysis (mJ) with different optimization methods

Optimization Methods	No. of. Vehicle Nodes				
	10	20	30	40	50
PSO	32	34	35	41	42
MOA	25	26	30	32	38
OOA	24	25	29	34	36
MDOOA	19	23	28	29	30

Table 4. Computational time analysis

Optimization Methods	Computational Time (ms)
PSO	120
MOA	110
OOA	90
MDOOA	75

In Figure 6, the throughput evaluation of MDOOA is compared with various state-of-the-art methods such as DEEC, LEACH, TDEEC, DDEEC, and CLEACH. The MDOOA achieved high throughput of 98.7kbps, 98.90kbps, 99.30kbps, 99.35kbps and 99.35kbps for different vehicle nodes from 10-50. High centrality enables effective data transmission in CH, which is needed to communicate data from BS to CH for enhancing throughput. The MDOOA demonstrates efficient performance in CH and routes through achieving high throughput. Table 2 presents the throughput analysis with different optimization methods. This analysis is determined using various vehicle nodes from 10 to 50 nodes. Compared to existing methods like Particle Swarm Optimization (PSO), Mayfly Optimization Approach (MOA), and OOA, the proposed MDOOA achieves a high throughput of 100 kbps for 50 vehicle nodes by balancing exploitation and exploration effectively, which allows it to rapidly converge to best solutions. The proposed method adaptive strategy increases the search process and manages intricate objectives efficiently.

Table 3 represents a performance analysis of EC with different optimization methods. The existing methods like PSO, MOA, and OOA are compared with the proposed MDOOA approach. The proposed MDOOA obtains a lesser EC of 19 mJ for 10 vehicle nodes because the proposed approach balances exploitation and exploration effectively, minimizing unnecessary energy compared to existing methods like PSO, MOA, and OOA, respectively.

Table 4 provides the performance of computational time analysis with different optimization methods. The proposed MDOOA achieves a less computational time of 75 ms compared to existing methods like PSO, MOA, and OOA. Due proposed approach effectively balances exploration and exploitation that accelerates convergence. Also, its adaptive mechanism reduces redundant calculations, which optimizes resource allocation in dynamic network conditions.

4.2. Comparative Analysis

The MDOOA comparative analysis with existing approaches such as IEAOCGO-C [22], PSO-SVNS-LBGB [23] and T2FSC-MOR [24] are discussed in this section. The comparison is simulated under various scenarios, as illustrated in Table 5. In Table 5, scenario 1 is IEAOCGO-C [22], scenario 2 is PSO-SVNS-LBGB [23] and scenario 3 is T2FSC-MOR [24]. The MDOOA is simulated based on the parameters listed in Table 5. In Tables 6, 7 and 8, MDOOA is compared with IEAOCGO-C [22], PSO-SVNS-LBGB [23] and T2FSC-MOR [24] respectively. These tables show that MDOOA performed better under various scenarios than existing techniques.

Table 5. Different scenario specifications

Parameters	Scenarios		
	1	2	3
Area	NA	1000×13000m	NA
Simulation time	NA	150s	NA
Packet size	NA	256bytes	NA
No. of vehicle nodes	20, 40, 60, 80, 100	100, 150, 200, 250, 300, 350	20, 40, 60, 80, 100

Table 6. Comparative analysis with IEAOCGO-C [22]

Scenario	Methods	Performance Metrics	No. of Vehicle Nodes				
			20	40	60	80	100
1	IEAOCGO-C [22]	Delay (ms)	6.06	6.16	6.44	7.28	7.79
		PDR (%)	99.38	89.36	83.40	76.07	74.21
		NLT (rounds)	5000	4700	4500	4200	4000
		EC (mJ)	30.96	51.68	70.19	84.91	90.33
		Throughput (kbps)	70.91	77.67	82.57	87.60	89.10
	MDOOA	Delay (ms)	3.53	3.67	3.82	4.12	4.39
		PDR (%)	99.54	99.21	98.76	98.43	98.06

		NLT (rounds)	5200	4900	4800	4600	4400
		EC (mJ)	25.37	38.61	46.95	52.74	68.31
		Throughput (kbps)	96.47	97.63	98.12	98.57	99.04

Table 7. Comparative analysis with PSO-SVNS-LBGB [23]

Scenario	**Methods**	**Performance Metrics**	**No. of Vehicle Nodes**					
			100	**150**	**200**	**250**	**300**	**350**
2	PSO-SVNS-LBGB [23]	PDR (%)	91.26	93.67	94.38	96.82	98.52	99.05
		EC (J)	0.019	0.026	0.034	0.043	0.056	0.062
		Throughput (kbps)	190.25	194.47	199.82	206.17	214.61	221.43
	MDOOA	PDR (%)	97.28	97.76	98.35	98.68	99.44	99.61
		EC (mJ)	0.016	0.022	0.028	0.032	0.035	0.039
		Throughput (kbps)	213.45	228.37	237.64	251.94	264.39	281.67

Table 8. Comparative analysis with T2FSC-MOR [24]

Scenario	**Methods**	**Performance Metrics**	**No. of Vehicle Nodes**				
			20	**40**	**60**	**80**	**100**
3	T2FSC-MOR [24]	Delay (s)	0.0810	0.1600	0.1770	0.2730	0.2570
		PDR	0.9300	0.8200	0.8000	0.7400	0.7200
	MDOOA	Delay (s)	0.0621	0.0937	0.1173	0.1359	0.1462
		PDR	0.9837	0.9783	0.9754	0.9721	0.9635

4.3. Discussion

The existing algorithms' limitations and the advantages of the proposed algorithms are discussed in this section. In EHACORP [21], objective functions were considered based on distance and energy, which does not consider centrality and LBF, which affects energy efficiency. IEAOCGO-C [22] increased sensitivity to parameter settings, requiring more extensive tuning to achieve optimal performance. T2FSC-MOR [24] does not perform cluster maintenance for balancing loads among clusters, which leads to node failure. OPRP [25] does not consider distance in the route path, which consumes high energy because the route has a high distance. To overcome these limitations, this research developed an MDOOA-based clustering and routing for increasing NLT and reducing EC in VANET. The distance between BS and CH and the distance between neighbor nodes, centrality, LBF, and energy are considered objective functions for CH and route selection. Additionally, CH maintenance is performed to balance loads among clusters, which is required to prevent node failure. By performing this process, the proposed MDOOA achieves a better performance. For example, the proposed MDOOA obtains better performance than T2FSC-MOR [24] due to the proposed method's adaptive decision-making capabilities that optimize multi-objectives like delay, energy consumption, etc. By using the dynamic behavior of osprey, the proposed MDOOA effectively explores the search space, which results in enhanced routing performance. Its ability to balance network load increases overall network lifetime and minimizes energy consumption.

4.4. Limitations

The MDOOA suffers from scalability issues in dense VANET or highly dynamic environments. As the network nodes and the number of vehicles increased, the MDOOA struggled to effectively process and adapt to rapidly changing topology, which resulted in delays in clustering and routing decisions. This process leads to suboptimal performance and enhanced communication overhead.

5. Conclusion

The MDOOA proposed in this research is based on energy-efficient clustering and routing in VANET. In the exploration phase, a dynamic, elite guidance mechanism with an adjustable ratio strategy is used to enhance the individual's search space exploration and avoid local optima issues at the beginning of the iteration. The MDOOA is used for CH and route selection with objective functions like the distance between BS to CH, the distance between neighbor nodes, centrality, LBF and energy, which gradually contributes to enhancing NLT.

Additionally, the CH maintenance is performed using MDOOA to balance loads among clusters, which is required to prevent node failure. The delay, PDR, NLT, EC and throughput are considered for experimental analysis of MDOOA. The MDOOA achieved significant improvements in delay, PDR, NLT, EC and throughput compared to the existing methods. The impact of this research is determined, and it provides practical implications for increasing traffic management and vehicular communication via enhanced clustering and routing in VANET. By advancing the field of Intelligent Transportation systems, this research contributes to developing safer and more responsive transportation networks. In future, advanced optimization methods with different fitness functions will be considered to solve scalability issues in dense or highly dynamic VANET environments.

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