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RVMF: RELIABLE ROUTING METHOD FOR VEHICULAR AD HOC NETWORKS USING MOTH-FLAME AND FIREFLY OPTIMIZATION ALGORITHMS

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ABSTRACT:

With the advancement of wireless communication technology, the intelligent transportation system (ITS) has attracted the attention of vehicle companies and academic researchers. Recently, vehicular ad hoc networks (VANETs) as a leading genuine technology have received serious attention as a kind of mobile ad hoc network (MANET) to ensure the safety of vehicles, drivers, and passengers. However, these networks face many challenges due to the mobility of vehicle nodes, wireless communication, and frequent topology changes. One of the crucial issues of these networks is a cluster-based routing scheme with the ability to provide quality of service (QoS) parameters. A clustering scheme is an appropriate method for increasing the scalability of VANETs. In a cluster-based routing scheme, the cluster head (CH) is responsible for receiving data from its member nodes, and aggregating and transferring data to the next CH node. On the other hand, providing a suitable clustering method is NP-hard problems and meta-heuristic algorithms are suitable for solving these problems. A scalable and reliable routing scheme is necessary and essential in VANETs. In this paper, a routing method based on the clustering technique is presented considering the moth-flame optimization (MFO) algorithm for clustering and the Firefly optimization algorithm (FoA) with a suitable fitness function for routing between CHs. The simulation of the proposed method with MATLAB software shows that the proposed RVMF method improves the parameters of packet delivery rate (PDR), latency, and throughput.

KEYWORDS: VANETs, Routing, Clustering, Moth-flame optimization algorithm, Firefly optimization algorithm.

1. INTRODUCTION

Recently, various important and innovative technologies such as the Internet of Things (IoT) (Jazebi & Ghaffari, 2020; Mousavi *et al.*, 2021), VANETs, and IoV (Internet of vehicles) play important roles in our daily life. The purpose of VANETs as an emerging technology and leading genuine technology is to disseminate information and data packets between vehicles and roadside unit (RSU) to improve the safety of roads, passengers, and drivers (Hamdi *et al.*, 2020; Zhang *et al.*, 2018). VANETs have various applications such as road traffic management, roadside commercial advertisement, and intelligent transportation (Boussoufa-Lahlah *et al.*, 2018). In all of these important and real-time applications, the messages must deliver to the destination node within a certain time limit (Belamri *et al.*, 2021). There are various types of data transmission methods in VANETs, including vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and hybrid communication (Das & Misra, *2018*).

In recent years due to the immense increase in the number of vehicle nodes, reliable, scalable, well-connected, and real-time data transmission schemes is a crucial issue in most applications of VANETs (Nazib & Moh, *2020*). Hence, providing a reliable and real-time routing algorithm is an essential and needed research topic in VANETs and ITS. On the other hand, VANETs have many important and crucial issues due to their dynamic topology change and wireless communication infrastructure (Ramamoorthy & Thangavelu, 2022). To transmit real-time data in VANETs, an efficient and reliable routing method is needed.

Routing schemes in VANETs are generally divided into five subcategories (Ghaffari, 2020): Location-based methods, path discovery methods, broadcast methods, infrastructure-based methods, and cluster-based schemes. Broadcast-based schemes for finding optimum route use broadcasting schemes. Broadcasting produces a large number of messages, which may increase the data transmission costs of VANETs. In position-based schemes for updating the routing table, frequent messages must be used to improve the accuracy of the data transmission scheme. Due to dynamic topology change in VANETs, using periodic and frequent messages increases the communication overhead in position-based routing schemes. Cluster-based routing schemes aggregate the received messages from the cluster members. This aggregation and data fusion operation can reduce the number of control messages. In a cluster-based routing scheme, CH nodes can aggregate the redundant control messages and data packets (Konduru & Sathya, 2022; Mukhtaruzzaman & Atiquzzaman, 2020). This reduction of control messages can improve the usage of network bandwidth (Mujahid, *et al.*, 2021). Due to vehicle node mobility and the fast expiration of data communication links, routing is one of the most significant challenges in VANETs. Improving the safety of passengers and drivers in VANETs is the main goal of the VANETs and for this reason, a QoS-based routing scheme is required (Bagherlou & Ghaffari, 2018; Belamri *et al.*, 2021; Ghaffari, 2020). QoS-based routing scheme can provide the goal of VANETs and improves the QoS parameters of the network. Recently, the most reliable routing schemes based on clustering techniques have been proposed for VANETs (Alaya & Sellami, 2021; Kudva *et al.*, 2021).

In this paper, a routing method based on the clustering technique will be presented using two metaheuristics moth-flame (Mirjalili, 2015) and firefly optimization (Yang, 2009) algorithms. The clustering process of vehicle nodes is an NP-hard problem and meta-heuristic techniques are suitable for solving NP-hard problems (Husnain & Anwar, 2022). Therefore, in this paper, we use the MFO for the clustering process (Clustering and CH nodes determination) of vehicle nodes. To choose the CH nodes, appropriate parameters such as link expiration time (LET), the

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relative speed of nodes, and Euclidean distance between nodes are considered with an appropriate fitness function. After the clustering process, routing is done using FOA based on an appropriate fitness function. Therefore, the main goal of this paper is to provide an appropriate and scalable routing protocol using MFO and FOA in VANETs. In the proposed RVMF method, the FOA will be used for finding the optimum route and routing process.

This paper provides the following contributions:

- It proposes a clustering scheme for VANETs using MFO.
- It considers various significant parameters for CH selection such as link expiration time, free buffer size, and Euclidean distance between vehicle nodes.
- It proposes a routing scheme using FOA and considers parameters for selecting the next CH node such as relative speed, delay, and distance between CH nodes.

The rest of the paper is organized as follows: The related works have been explained in Section 2. Section 3 indicates the proposed scheme. The performance evaluation of the proposed scheme has explained in Section 4. Finally, Section 5 concludes the paper.

2. RELATED WORKS

In (Divya, *et al.,* 2021), the authors proposed a Clustered Vehicle Location scheme using Hybrid Krill Herd and Bat Optimization (CVL-HKH-BO) method to detect and prevent black hole and wormhole attacks using an appropriate fitness function. For improving energy consumption and packet delay, the authors used the CVL method. Simulation results indicate that CVL-KHB-BO improves QoS parameters such as energy consumption, packet overload, and delay. In (Abbas & Fan, 2018), the authors proposed a new clustering-based reliable low-latency multipath routing (CRLLR) using AOMDV (ad hoc on-demand multipath distance vector) and Ant Colony Optimization (ACO) algorithm. For CH node selection, they considered link reliability as a main parameter. For improving the QoS parameters, they used the ACO method to obtain the optimal and appropriate paths in VANETs. The main disadvantage of this scheme is the high overhead. Highly overhead schemes cause congestion occurrence in VANETs.

In (Kudva *et al.,* 2021), the authors proposed a routing protocol based on a clustering technique using a modified K-Means technique. The authors combine a maximum stable set problem with a continuous Hopfield network for choosing essential input metrics of the K-Means method, the authors use a maximum stable set problem and continuous Hopfield network. They use important metrics such as distance and link reliability in the K-Means method to assign vehicle nodes to each cluster as a cluster member node. Finally, the CH vehicle node is selected using the proper fitness function considering the velocity, the amount of free buffer space, and the degree of each node. Simulation process results have indicated that this scheme improves different QoS parameters such as traffic congestion, PDR, throughput, and timeliness.

In (Raja, 2021), the PRAVN scheme a perspective routing scheme was proposed for VANET-WSN architecture. PRAVN is a cluster-based routing protocol. This scheme performs the clustering process using the improved water wave optimization (IWWO) method and multi-constraint features. For routing purposes, the authors used the rider optimization (RO) scheme for next-hop node selection, which provides the lifetime of VANETs and lossless connection.

In (Kheradmand, *et al.,* 2022), the authors presented a Traffic-aware and Low-Latency cluster-based Routing Scheme (TaLAR) in VANETs. In TaLAR, for the clustering process, the authors select CH nodes using the Harris Hawks optimization (HHO) algorithm. To choose the CH vehicle nodes different parameters were considered such as intra-cluster distance, link reliability, and velocity of vehicles. After the clustering process, TaLAR selects the next appropriate CH node for transmission data using the HHO algorithm considering the link reliability and inter-cluster distance. Simulation results indicate that TaLAR improves QoS parameters in comparison with other schemes. In (Azhdari et al., 2022), authors proposed a routing scheme using the fuzzy logic technique with authentication capability in VANETs. In the clustering phase, vehicle nodes are clustered. For the routing process, the authors divided the data packets into two types: immediate and ordinary. The immediate data type should be sent in a real-time manner and immediately. On the other hand, any data packet type is classified into two categories: simple packet and secure packet. A simple type of data packet does not need any authentication technique. But the secure type of data packet needs an authentication technique using an authentication code and symmetric cryptography algorithm.

In (Darabkh, *et al.,* 2022), the authors presented ICDRP-F-SDVN (Innovative Cluster-Based Dual-Phase Routing Protocol Using Fog Computing and Software-Defined Vehicular Network) an efficient routing scheme for VANETs. The combination of fog computing techniques and Software-Defined Networks (SDN) provides a simple, reliable, and flexible infrastructure that overcomes issues arising from new technological development and rapid escalation in the number of smart vehicles. Also, the authors presented a new scheme for choosing CH vehicle nodes and cluster member nodes for each cluster. This scheme uses traditional AODV protocol as a redundant scheme when the SDN fails to deliver packets.

In (Mohammadnezhad & Ghaffari, 2019), the authors presented RBF-ICA, a routing method using a clustering technique for VANETs using meta-heuristic algorithm ICA (imperialist competitive algorithm) and RBF (radial basis function) neural networks. For clustering the vehicle nodes, the authors used ICA with appropriate fitness functions. This object function considers node degree and speed of nodes as important parameters. Then, the CH node is selected using RBF neural network algorithm considering different factors such as the free buffer space of each node and expected transmission count. For the routing process, the gateway and next CH nodes were selected considering route request and route reply messages. The authors have claimed that they have improved the QoS parameters such as average end-to-end delay, PDR, and throughput.

In (Nahar & Das, 2023), the authors proposed MetaLearn, which employs a parameterized approach to remove future rewards uncertainty as well as vehicular state exploration to optimize the multilevel VANETs structure. MetaLearn searches for the optimum solution using Grey Wolf Optimization (GWO) and Temporal Difference Learning. MetaLearn method enables CH nodes to learn how to adjust route request forwarding according to QoS parameters. The input received by a vehicle from previous evaluations is used to learn and adapt the subsequent actions accordingly. Furthermore, a customized reward function is developed to select the CH and identify stable clusters through GWO.

In (Hamdi, Audah, & Rashid, 2022), using the adaptive jumping multi-objective firefly algorithm (AJ-MOFA), the authors proposed a cluster-based routing protocol for VANETS. Then, the authors integrated AJ-MOFA with a clustering and forwarding mechanism (CFM). This scheme consists of three main components. The first is clustering, which uses arbitration based on the CH node score; the second is a forwarding component that uses probabilistic forwarding and the third is AJ-MOFA. The solution space design in CFM combined the probability of forwarding and the maximum number of nodes within one cluster. Simulation results showed that both AJ-MOFA and CFM with benchmarks using multi-objective optimization and networking metrics improve the QoS parameters.

In (Behura *et al*., 2022), the authors used Giraffe kicking optimization (GKO) and proposed an energy-efficient routing scheme for WSN (Wireless sensor network) based VANETs. They used C-means-based GKO algorithm to avoid a large amount of energy consumption triggered by the redundant sensor nodes. To improve the QoS parameters, it is essential to awake the minimum number of sensor nodes to consume less energy in the network by using optimized clustering techniques. For this challenge, the authors have planned a hybrid C-means Giraffe optimization technique with a multi-fitness function used to reach efficient routing enactment in VANET.

In (Moridi & Barati, 2017), the authors proposed a reliable multi-level routing protocol using tabu search (RMRPTS) for VANETs based on clustering. This protocol is an extension of ad hoc on-demand distance vector (AODV) routing protocol that has been improved using fuzzy logic in order to create reliable routing between cluster members. For routing process between CHs and destination, they used tabu search algorithm. They have considered effective parameters to select the best route include nodes distance, the velocity of nodes, node's angle, link stability, and link reliability.

Based on above mentioned related works, routing is hot and timely research topics for VANETs. With immense increasing the number of vehicles, providing a new routing scheme for VANETs is essential.

3. PROPOSED SCHEME

In the proposed method, Moth-flame optimization algorithm uses for clustering process and CH nodes determination. After clustering phase, firefly optimization algorithm uses for routing process and finding appropriate route between origin and destination vehicle nodes. Various and important parameters have been used to select the optimum CH nodes in the proposed RVMF method. In the proposed RVMF scheme, the number of CH nodes is equal to 5% of the total vehicle nodes. After selecting suitable cluster head nodes, the members of each cluster are determined and assigned to each cluster. After the clustering process, routing process is done using the firefly optimization algorithm, which determines the next proper CH node. The proposed RVMF method includes two phases: clustering and routing. In this section we will explain each phase of the proposed scheme in details.

3.1 Clustering phase

For clustering process, the CH nodes are determined first, and then each CH node chooses its members based on appropriate parameters by advertising itself as the CH node. Each CH node advertises itself as CH node and the other vehicle nodes send assignment message to appropriate CH nodes considering the distance parameter. The description of the parameters considered for CH selection is given below:

- Link expiration time

Due to mobility and high speed of vehicle nodes, the link expiration time (LET) is considered as an important parameter in determining cluster head nodes for VANETs. Among vehicle nodes, the expiration time of the communication link between two vehicles in VANETs is defined as the time that two vehicle nodes communicated with each other. Two nodes with a higher communication link expiration time between two vehicles means that they can communicate with each other longer than those in the opposite direction, and therefore those vehicle nodes can transmit messages with less packet loss. It is possible to estimate the expiration time of the communication link between two vehicles with location information and speed information. Assume that R is the radio range of each vehicle node in VANET. $dis(v_a, v_b)$ is the Euclidean distance between two vehicle nodes v_a and v_b. Maximum value for LET is appropriate for selectin CH nodes. The link expiration time between two vehicles v_a and v_b is indicated as $LET(v_a, v_b)$ and is calculated using Eq. (1) as follows (*Namboodiri & Gao, 2007*).

$$Max\ f_1 = LET(v_a, v_b) = \frac{R+\delta\times dis(v_a,v_b)}{|v_a - v_b|} \tag{1}$$

In Eq. (1), $\delta \in \{-1, 0, 1\}$. In this equation, if $\delta = 1$, the two vehicle nodes are moving toward each other. If $\delta = -1$, two vehicle nodes are moving away from each other and otherwise $\delta = 0$.

- Euclidean distance between CH and cluster members

Euclidean distance directly relates to data transmission delay between two vehicle nodes in VANETs. Hence, short Euclidean distance between nodes can reduce data transmission delay in real-time applications in VANETs. The distance between the cluster members and the corresponding CH node is a suitable parameter for choosing the optimal CH node. The Euclidean distance between two vehicles i and j with coordination $(x_j, y_j)$and (x_i, y_i) is obtained from Eq. (2) as follows:

$$dis(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{2}$$

Considering that the Euclidean distance between two mobile nodes plays an essential role in determining the CH node, nodes will be selected as the CH whose average distance between them and the CH node is minimum. On the other hand, to maximize the value of Eq. (3), the value of function f_2 can be determined from Eq. (3). In this regard, the average distance between the members of a CH node and the corresponding CH is calculated for all clusters.

$$Max\ f_2 = \frac{1}{\sum_{j=1}^{m}[\frac{1}{l_j}\times\sum_{k=1}^{l_j} dis(v_k, CH_i)]} \tag{3}$$

where in Eq. (3), m and l_j are number of clusters and vehicle nodes, respectively. In Eq. (3), $\sum_{k=1}^{l_j} dis(v_k, CH_i)$ is the sum of Euclidean distance between each vehicle node and its related cluster head.

- Free buffer size

In Eq. (4), f_3 indicates the free buffer size of each vehicle. If the amount of free buffer size of a node is more, that node is suitable for the CH candidate node. Because in case of congestion in network, a node with a larger amount of free buffer will refrain from discarding the packet and can keep the packet in its buffer until the congestion is resolved. Congestion will cause packets to be dropped and the dropped packet should be retransmitted. On the other hand, retransmitting the lost packets will increase congestion again. Hence, vehicle nodes with maximum free buffer space are appropriate as cluster head candidate.

$$Max\ f_3 = \sum_{j=1}^{m} FB_{CHj} \tag{4}$$

- Fitness function for selecting CH nodes

The fitness function of the proposed method for selecting the CH nodes is Eq. (5) and the objective is to maximize the value of this function. Therefore, all the components of this function must also have their maximum value:

$$Max\ F = \alpha \times f_1 + \beta \times f_2 + \gamma \times f_3 \tag{5}$$

In Eq. (5), parameters α, β and γ are weight parameters and their sum is equal to 1. Function f_1 shows the expiration time of the communication link between two vehicle nodes, f_2 shows the average distance between the nodes and the CH node, and f_3 shows the free buffer size. All the functions are normalized using Eq. (6). On the other hand, different parameters should have the same effect on the selection of the cluster head. For this reason, in the proposed method, the value of each parameter must be between 0 and 1.

$$F(x) = \frac{f_i - f_{min}}{f_{max} - f_{min}} \tag{6}$$

In Eq. (6), f_i is the main value of each parameter, f_{min} is the minimum value, f_{max} is the maximum value and F(x) is the normal value, whose value is between 0 and 1. After CH selection phase each CH nodes advertise itself to choose the member nodes of each cluster. According to its distance to each CH node, each vehicle requests membership to that CH node. Therefore, the clustering stage, which means determining the CH node and its members, ends at this stage. After some time, according to the speed of the moving vehicles, the clustering process will be repeated again. Algorithm 1 shows the pseudocode for selecting CH nodes.

Algorithm 1. Pseudocode for selecting CH node

```
Input: vehicle nodes V: {V1, V2, … VN}
Output: appropriate CH nodes
Initialize required parameters for clustering phase
  for each vehicle node V do
    calculate the fitness function for selecting CH nodes
    if V≠N
      CH node= Maximum value of F (Fitness function)
    end if
  end for
```

3.2. Routing process

A suitable routing method is required to send the data packets with the lowest delay and the lowest loss rate. The source node transmits data packets to its corresponding CH node. If the destination is in the CH's routing table, the node delivers it. Otherwise, it finds a suitable CH among the neighbouring CHs and sends the packet hop by hop to be delivered to the destination. How to determine the next hop or the next CH node is examined in this section. Routing process is done using the firefly optimization algorithm for selecting the proper neighbour CH node.

For routing process and to select the next appropriate CH node, the following parameters are used in the proposed method: (a) relative speed of vehicle node (b) delay and (c) distance between member nodes and CH. Each parameter is explained as follows:

- Relative speed

Relative speed is one of the important parameters for VANETs. In Eq. (7), RS_{ij} is the relative speed, which is measured using RS_{ij}, the relative speed and the maximum speed of vehicles (V_M), as follows:

$$Min\ h_1 = RS_{ij} = \frac{S_{ij}}{V_M} \tag{7}$$

$$S_{ij} = \begin{cases} \sqrt{{V_i}^2 + {V_j}^2 - 2V_iV_jCOS\theta}, & \\ V_i - V_j, & \theta = 0 \\ V_i + V_j, & \theta = 180 \end{cases} \tag{8}$$

In Eq. (7), S_{ij} is the relative speed between nodes i and j, which is measured using Vi, Vj, and θ. In Eq. (8), Vi and Vj are the velocity of adjacent and source vehicle nodes, respectively. θ is the angle between the sending vehicle and the receiving vehicle. According to Eq. (8), if the value of this angle is equal to zero or 180 degrees, the value of this speed will be equal to the difference and sum of these speeds, respectively.

- Euclidean distance between CH nodes

Euclidean distance is an important parameter for minimizing the timeliness metric in each path and can be calculated as follows using Eq. (9).

$$Min\ h_2 = D_v = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{9}$$

- Fitness function for the routing process

For improving the QoS parameters and selecting proper next CH node, we define an objective function for minimizing H function such as Eq. (10).

$$Min\ H = \mu \times h_1 + (1 - \mu) \times h_2 \tag{10}$$

where in Eq. (10), µ is weighting parameter and its value is between 0 and 1. Using Eq. (6), we can normalize the Eq. (10). The route request (RREQ) message includes different fields such as RREQ ID, vehicle speed, link expiration time, source address, destination address, hop count, node coordination, and mobility direction. Each vehicle node sends RREQ message for finding reliable and real-time path. Figures 1 and 2 indicate the architecture and flowchart of the presented scheme. In the architecture of the proposed RVMF scheme, after clustering phase, the CH node can determine the appropriate next CH node for routing and data transmission in hop-by-hop manner.

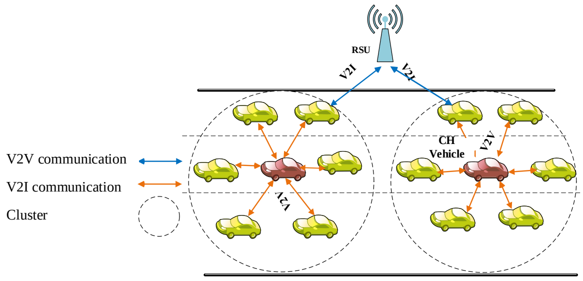

Figure 1. The architecture of RVMV method

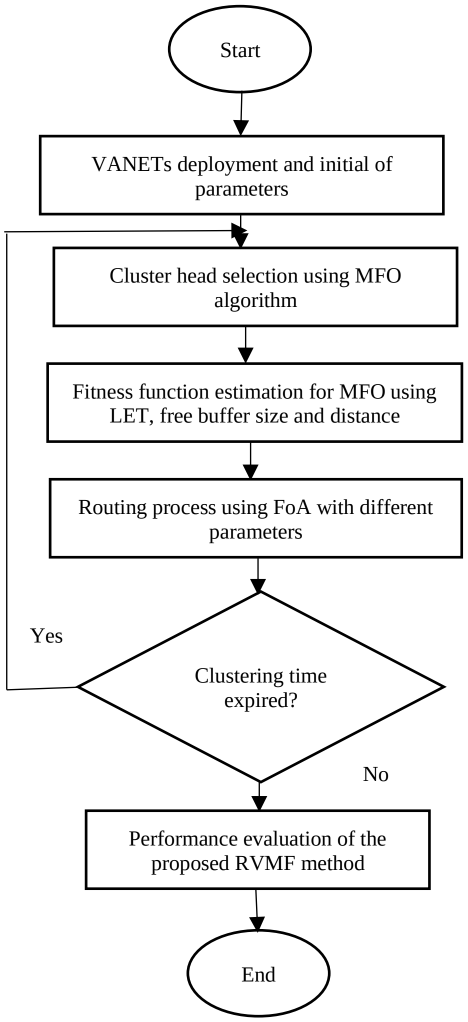

Figure 2. Flowchart of the proposed RVMP scheme

Algorithm 2 shows the pseudocode of the proposed RVMF method.

Algorithm 2. Pseudocode of the proposed RVMP scheme

```
Input: number of nodes, Relative speed, Link expiration time, Free buffer size, Distance
Output: optimal selection of cluster heads= {CH1, CH2, …CHm}
For i=1 to m do
   Calculate fitness function for CH selection using Eq. (5)
   CHi nodes= m nodes with max (fitness function)
End for
Select next best CH node using FOA
For hop= 1 to N do
    If dest_node_address is in routing table of CH
        Deliver data to the destination node
    Else select next best CH node
    End if
End for
End
```

4. PERFORMANCE EVALAUATION

The proposed RMVF scheme was simulated in MATLAB software. We used a 10 Km highway scenario with 2 lines number and a variable number of vehicle nodes (100 to 350) and an average vehicle node velocity (60 Km/h to 120 Km/h). In the simulation scenario, radio range of each vehicle is 300 m and the size of data packet is 1 KB. Table 1 indicates the value of the simulation parameters.

In the simulation phase, the performance of the proposed method was compared with RMRPTS (Moridi & Barati, 2017) scheme. The RMRPTS scheme is very similar to the proposed scheme and both of these schemes use metaheuristic algorithms for routing process in VANETs. Two schemes are cluster-based routing scheme for VANETs and were compared with each other using the same simulation parameters.

The performance metrics of the proposed RMVF method for examination are PDR, throughput, and latency. In this section, we explain each parameter in details.

Table 1. Simulation parameters value

Parameter	Value
Network area	10 Km
Line number	2
Vehicle number	100, 150, 200, 250, 300, 350
Speed	60 -120 Km/h
Radio range	300 m
Packet size	1 KB
Simulation time	100 sec
α, β, γ,μ	0.4, 0.4, 0.2, 0.6
Simulation time	300 Sec
Number of simulations	20

4.1. PDR

PDR is an important QoS parameter for evaluating the performance and reliability of a routing scheme. Network congestion and link breaking are the main reasons for packet loss or packet dropping. PDR is the ratio of the number of successfully received packets in destination node to the total number of packets generated in the network. Eq. (11) shows the packet delivery rate.

$$PDR = \frac{\sum \text{Total number of packets received}}{\sum \text{Total number of packets send}} \times 100\% \qquad (11)$$

Figure 3 shows the average PDR based on the number of network nodes. PDR is a very important parameter for quality of service. From Figure 3, we can conclude that the proposed RMVF method has a higher delivery rate compared to the other method. The reason is that the proposed method considers the capability of free buffer size and link reliability or link expiration time to select the CH node. These parameters can improve the PDR parameter. Because packets are lost due to network congestion and communication link expiration time, which happens less in the proposed RMVF method. On the other hand, considering the relative speed for CH node selection can increase the PDR metric in the proposed method. On the other hand, using combination of MFO and FOA for clustering and routing processes in the proposed RMVF method have noticeable impact on the PDR parameter of the proposed scheme.

According to the result of the Figure 3, with the increase of number of network nodes, there is no noticeable change in the PDR, which shows that the proposed method has good scalability. Loss of critical packets in critical applications can cause many problems for VANETs. Because the purpose of these networks is to send real-time data packets in critical applications. Therefore, increasing the PDR in the proposed method can be considered as one of the advantages of this method.

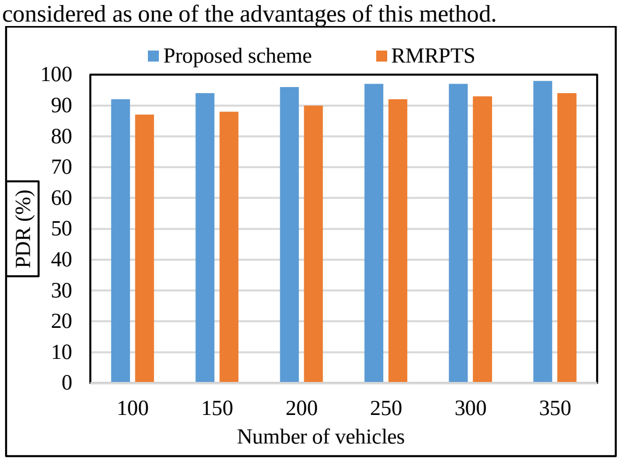

Figure 3. PDR versus the number of vehicle nodes

4.2. Throughput

Throughput is another important QoS parameter in performance evaluation of a routing protocol. Network throughput is the number of successfully transmitted bits per network simulation time. Eq. (12) calculates the throughput of the proposed RMVF method as follows.

$$\text{Throughput} = \frac{\sum \text{Total number of packets received}}{\sum \text{Total time of simulation}} \qquad (12)$$

Figure 4 shows the throughput based on the number of network nodes. As Figure 4 shows, the throughput of the proposed RMVF method is good.

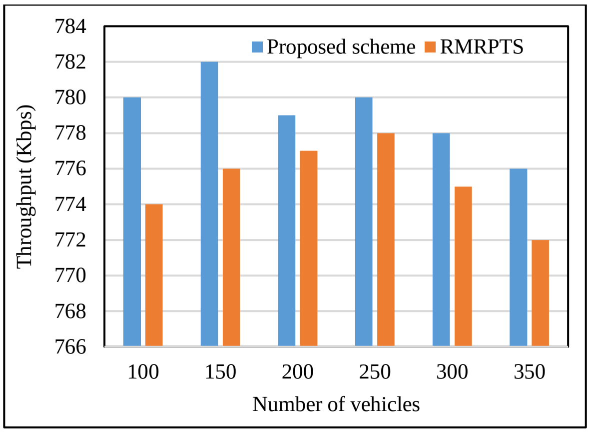

Figure 4. Throughput

4.3. Average end-to-end delay

Data transmission delay is one of the most important parameters in most critical and real-time applications and routing protocols of VANETs. In real-time applications, if the time limit for sending the packet is not respected, it will cause many problems. In the proposed method, by considering the parameter of distance between nodes and relative speed for selecting the CH nodes and clustering process, and considering the distance in choosing the next hop for sending the packet and routing process, it can reduce the average end-to-end delay. On the other hand, as Figure 5 indicates, the average end-to-end delay increases in the proposed RVMF method, which is due to the occurrence of network congestion. Congestion causes the packet to be lost and retransmitted, which again increases the transmission delay.

$$\text{ETE} - \text{delay} = \frac{\sum \textit{Total time spent to deliver packets}}{\sum \textit{numberof packets}} \quad (13)$$

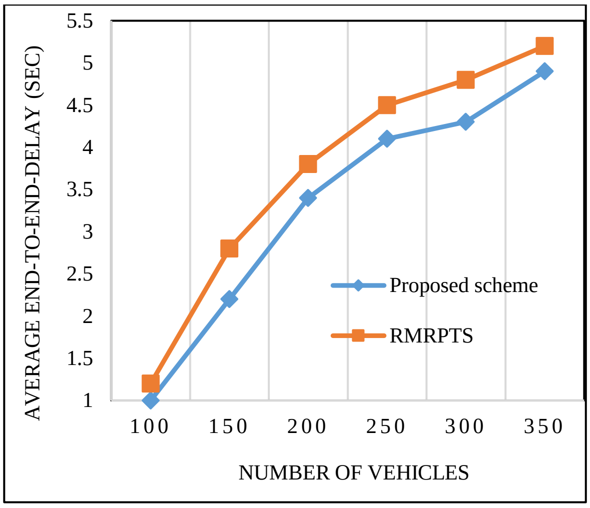

Figure 5. Average end-to-end delay

5. CONCLUSION

In recent years, VANETs have important role in our daily life. Despite ensuring the safety of passengers and drivers, VANETs face many challenges. These challenges arise from using wireless communication channel, frequent changes in network topology, and mobility of vehicle nodes. For real-time and critical applications, providing appropriate and reliable routing scheme is considered one of the basic challenges of these networks. In this paper, a routing method based on clustering using MFO algorithm and FOA method is presented. For the clustering of nodes, the MFO meta-heuristic algorithm with a suitable fitness function has been used. In the mentioned fitness function, link expiration time, the velocity of the vehicle nodes, the amount of free buffer of the nodes and the distance between the members and the CH nodes are considered. For routing between the CH nodes of the clusters, the FOA has been used, considering the distance parameter. Simulation results of the proposed method RVMF in MATLAB software show that RVMF improves the QoS parameters such as throughput, average end-to-end delay, and PDR. As a future work, the use of the software-defined network (SDN) or the use of game theory can help to identify appropriate and reliable routes in VANETs.

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