Quasi Oppositional Artificial Fish Swarm Optimization Based Multi-Hop Routing Protocol for Vehicular Adhoc Networks

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Abstract

Vehicular Adhoc Networks (VANET) is a technology which utilizes moving vehicles as nodes to deploy a mobile network. Since the vehicles move frequently, a challenging issue lies in the design of robust routing techniques to optimize routes. At the same time, routing becomes a tedious process as there is no specific node responsible to identify and direct the routes amongst the nodes. Therefore, an ideal routing protocol becomes essential to improve resource utilization in VANET. This study designs a new quasi oppositional artificial fish swarm optimization based multi-hop routing protocol (QOAFSA-MRP) for optimal route selection in VANET. The QOAFSA technique involves the integration of quasi oppositional based learning (QOBL) with traditional AFSA to enhance the convergence rate. Besides, a weighted clustering scheme is designed to organize clusters in the network. Moreover, the QOAFSA-MRP technique derives a fitness function involving diverse network parameters for effective selection of routes to destination. For evaluating the better performance of the QOAFSA-MRP technique, a comprehensive simulationanalysis is performed and the results are inspected under varying aspects. The obtained experimental values pointed out the supremacy of the QOAFSA-MRP technique over the other techniques.

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1. Introduction

A vehicular ad hoc network (VANET) enables transmission among infrastructure and vehicles or between vehicles [1]. The concept of having inter-vehicle transmission linked to a wired network has been studied in the year of 1980. In VANET, we could attain conventional security applications like red light warnings, collision, and icy roads, along with non-safety applications like reservation query, camera picture feed traffic information dissemination, etc. In recent times, there is an evolving trend of using mobile transmission to environmental challenges [2]. It can be feasible to attain essential data from VANET to enhance the applications of gas or another asset. If there is insufficient roadside unit (RSU) or direct transmissions among distant vehicles are preferable, it generally takes one more step of vehicle-to-vehicle (V2V) transmissions for transmitting data from a specific source to destination [3]. The broadcast range of radio devices is usually 100–200 m for V2V, i.e., lesser when compared to the dimension of the extensive region. Authors have extensively investigated thesemultihop transmissions not only because VANET application has a huge potential market, but also, they are scientifically interesting [4]. It has become highly complex to improve parameters of a VANET because of its high mobile nature. Connections could be frequently disconnected that is sometimes not possible to precisely cast the presence of end-to-end connections. Consequently, carry-and-forward type heuristic models have been largely employed for routing packets on multihop transmissions in VANET. Geographical forwarding was initially presented as GPSR [5]. The results have been discussed in several studies which try to find an outstanding efficiency using common methodologies. One of them, named PBRV, solves the routing loop challenges of GPSR.

VANET is projected and adopts distinct varieties of routing techniques, like reactive, proactive, geographic, and hybrid based routing technique [6]. The reactive and proactive routing techniques have been categorized into the topology-based routing techniqueclass that aim is to find the path stuck amongst the source and destination beforehand initiating the data transmitting [7]. The major distinction among the 2 is that the proactive routing technique begins a path finding to each node situated in the whole network, producing an end-to-end delay and increase in control overhead [8]. Whereas, in reactive routing technique, a source node begins a path finding procedure for reaching only the preferred destination. This method decreases the control overhead, but the path finding procedure is needed in discovering a path for all the nodes. The hybrid routing technique integrates the features of reactive and proactive routing techniques. The node in hybrid networks are gathered in a certain region is known as cluster [9]. Hybrid routing technique, occasionally known as Cluster-Based Routing (CBR) technique, has been developed for improving scalability of the network by enabling the nodes within the cluster to transmit via a pre-selected Cluster Head (CH) with proactive routing techniques [10]. But, in the event of communications sandwiched between clusters, reactive routing techniques are triggered.

This study designs a new quasi oppositional artificial fish swarm optimization based multi-hop routing protocol (QOAFSA-MRP) for optimal route selection in VANET. The QOAFSA technique involves the integration of quasi oppositional based learning (QOBL) with traditional AFSA to enhance the convergence rate. Followed by, a weighted clustering scheme is designed to organize clusters in the network. Furthermore, the QOAFSA-MRP technique derives a fitness function involving diverse network parameters for effective selection of routes to destination. For examining the improved outcomes of the QOAFSA-MRP technique, a wide-ranging simulation analysis is executed and the results are examined under varying aspects.

2. Literature Review

In Al-Shaibany[11], a proposed novel clustering formation method, which focuses on the stability of CHs and gateway. Also, it focuses on the stopped and parked vehicles to be gateways and CHs. Furthermore, a novel cluster based routing technique to construct an optimum route with maximum stability and minimum delay known as CRDS is recommended for security applications. CRDS is based on the proposed clustering method and calculates the optimum paths based on a newly proposed optimization method. Aravindhan and Dhas[12] proposed 2 soft computing methods: In the beginning, a hybrid clustering method is presented that integrates the geographic and context based clustering methods. The hybrid clustering decreases the traffic and control overhead in the network. Next, the destination aware routing technique has been presented for intercluster routing that reduces the end-to-end delay and enhances the total packet delivery ratio.

Fatemidokht and Rafsanjani [13], proposed a clustering routing technique, known as QMM-VANET, that consider QoS requirement mobility constraints, and the distrust value parameter. This technique defines the stable and reliable cluster and enhacnesthe connectivity and stability at the time of transmission. This technique is consist of 3 portions: (1) electing a trustier vehicle as a cluster-head and computing the QoS of vehicles, (2) electing an appropriate neighbouring node as gateways for re-transmitting the packet, and (3) utilizing gateway recovery method for selecting other gateways in case of connection failure. Baoet al. [14], proposed an Effective Clustering V2V Routing Based PSO in VANET (CRBP). In the beginning, vehicle node with similar moving direction is determined and the CHs are chosen. Next, for the necessary routing optimization, the fitness function, route particle velocity, coding rules, and iteration rules are developed. Then, the approaches which could obviously enhance the routing efficacy in the cluster and amongst clustersare projected. Lastly, NS3 and SUMO are utilized for stimulating and analyzing the efficiency of the CRBP.

Elhoseny and Shankar [15] proposed K-Medoid Clustering method for clustering the vehicle node and then, energy effective node is identified for compelling transmission. Using the anticipation of achieving energy effective transmission, effective node is identified from all the clusters by a Metaheuristic model, e.g., EDA that enhances the parameter as minimal power utilization in VANET.In Manickam et al. [16], secure information could be transferred via VANET, LEACH technique based clustering, and Light Weight cryptographically method is taken into account. Initially, sorting the vehicles into clusters and grouping the networks through the cluster is a standout among the most adequate and most comprehensive manners. This method provides a solution for controlling the attacks over the VANET security. Enhance the security dimension of data transmitting via network structure the stimulated RFF improvement utilized to find the consistent vehicles in designed VNET topology.

Cheng et al. [17] present a connectivity prediction based dynamic clustering (DC) method for VANET in an urban environment. Initially, propose a connectivity prediction model (CP) depends on the vehicle node features and relative features amongst vehicle nodes. Next, create a DC method on the basis of connectivity between vehicle node density and vehicle nodes. Lastly, propose a DC method based routing model for realizing stable transmissions amongst vehicle nodes. Kolandaisamy et al. [18] projected a Stream Position Performance Analysis (SPPA) method. This method monitors the location of field station in transmitting the data to execute DDoS attacks. The approach computes several aspects such as Attack signature sample rate (CCA), Conflict field, and Conflict data. With these aspects, the technique recognizes the reliability of the packets and includesthem in decision making.

In Singh et al. [19], a proposed discrete simulator of event for estimating the average amount of concurrently transferring nodes, a functional channel method to the VANET, and a technique of assessing node density. This method depends on any equation to permit separate nodes to evaluate their nearby node density in realtime Optimized Node Cluster Algorithm using Network Density where the composition of a cluster has been triggered, this traffic signal is similar and is established mainly on the location a vehicle may take well afterward crossing.

In Yang and Zhang [20], a proposed clustering routing technique based segmentation (CRPBS) in the VANET. The size of the cluster is fixed in the transmission section, the sections are separated into blocks of equivalent size based on the vehicle density in all the clusters, and later the CHs for transmitting the data packet is defined on the basis of maximal lifetime principle in the block with the minimum waiting time. Sabbagh and Shcherbakov[21] present a stable and secure routing technique that incorporates the feature of clustering method and CSA to determine a stable efficient and secure routing. In this presented model, k-means clustering is utilized for cluster formation and a CSA is utilized to select the CHs. The election of CH is based on 5 weight parameters, the primary one is speed of node and trust factor with neighbourhood nodes.

3. The Proposed Model

In this study, a novel QOAFSA-MRP technique is derived for multi-hop routing in VANET. The proposed QOAFSA-MRP technique initially executes the WCS to choose the CHs proficiently. Followed by, the QOAFSA technique is employed to effectively select the optimal set of routes to destination. Fig. 1 illustrates the overall block diagram of proposed QOAFSA-MRP model. The detailed working of each module is offered in the succeeding sections.

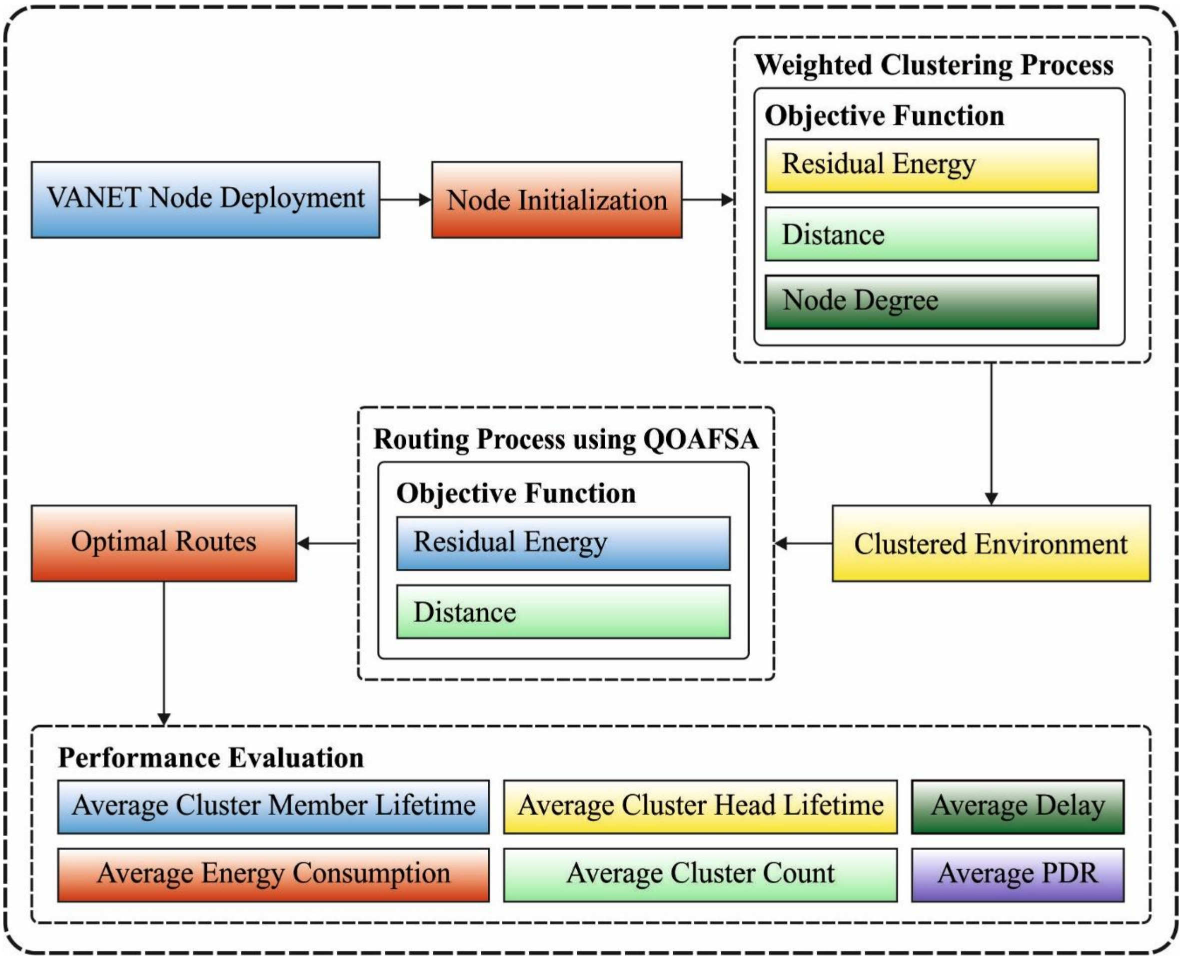

Fig. 1. Block diagram of QOAFSA-MRP model

3.1. Weighted Clustering Technique

The weighted clustering approach defines the CH and applies cluster structure utilizing 3 measures as RE (Er_i), distance (D_i), and node degree (ND_i). To all the nodes, the weight $P_i$is computed as per the executed function:

$$P_i = w_1 * Er_i + w_2 * D_i + w_3 * ND_i \tag{1}$$

where w_1, w_2 and $w_3$refers the coefficients of model condition

$$w_1 + w_2 + w_3 = 1 \tag{2}$$

3.2. Design of QOAFSA technique for Route Selection Process

AFSA ensures a global optimal solution search problem [22], i.e., very important in artificial intelligence to execute behavioral modelling. Assume a swarm consist of N artificial fishes and a state vector $X = (x_1, x_2, \ldots x_n)$, whereas n states/attributes of the artificial fish are to be improved through the AFSA process. Additionally, assume that $Y = f(X)$ signifies the objective function providing the food concentration of the artificial fish at the existing position, and $Dij = ||X_i - X_j||$ be utilized for describing the distance among artificial fishes i and j. Another significant parameter for the artificial fish, include its maximal steps for movement, vision domain, maximal attempts in every praying, and the congestion factors, are also taken into account and are stated as visual, step, $\delta,$ and try number, correspondingly. For best result, the congestion factor is utilized to limit the size of the artificial swarm. The behavior of the artificial fish is defined as chasing, praying, and swarm.

Praying

When the artificial fish is currently in state X_i, to execute praying, then it should choose other states, for example, X_j, i.e., placed within its visual field. Then, the search for a minimum solution is repeated till $Y_i \geq Y_j$, in such cases, praying can be achieved by moving one step in the direction. But, when $Yi \leq Yj$, other statesX_j should be re-selected from the visual field arbitrarily to examine it could forward according to specific forwarding conditions. This method is continued for try-number times, and the still forward motion criteria are not fulfilled, it would take one step in an arbitrary direction. Arithmetically, it is formulated by

$$x_{i-nexi-k} = x_{i\to k} + \frac{x_{jk} - x_{ik}}{\|X_j - X_i\|} * random(step) Y_j > Y_i, \tag{3}$$

$$x_{i-next-k} = x_{i\to k} + random(step) Y_j \leq Y_i,$$

whereas $k = 1,2 \ldots n, x_{ij}$ denotes the kth element of X_i, i.e. the present state of the artificial fish; x_{jk} denotes the kth component of X_j, i.e., the state of the artificial fish afterward random movement, and $x_{i-nexi-k}$ signifies the kth component of x_{i-next}, i.e., the following state of the artificial fish. Likewise, Y_i&Y_j represent the value of the objective function of the present state and that afterward a random movement, correspondingly and random(step) signifies a random number chosen from the range determined as [0 steps]. Fig. 2 demonstrates the flowchart of AFSA.

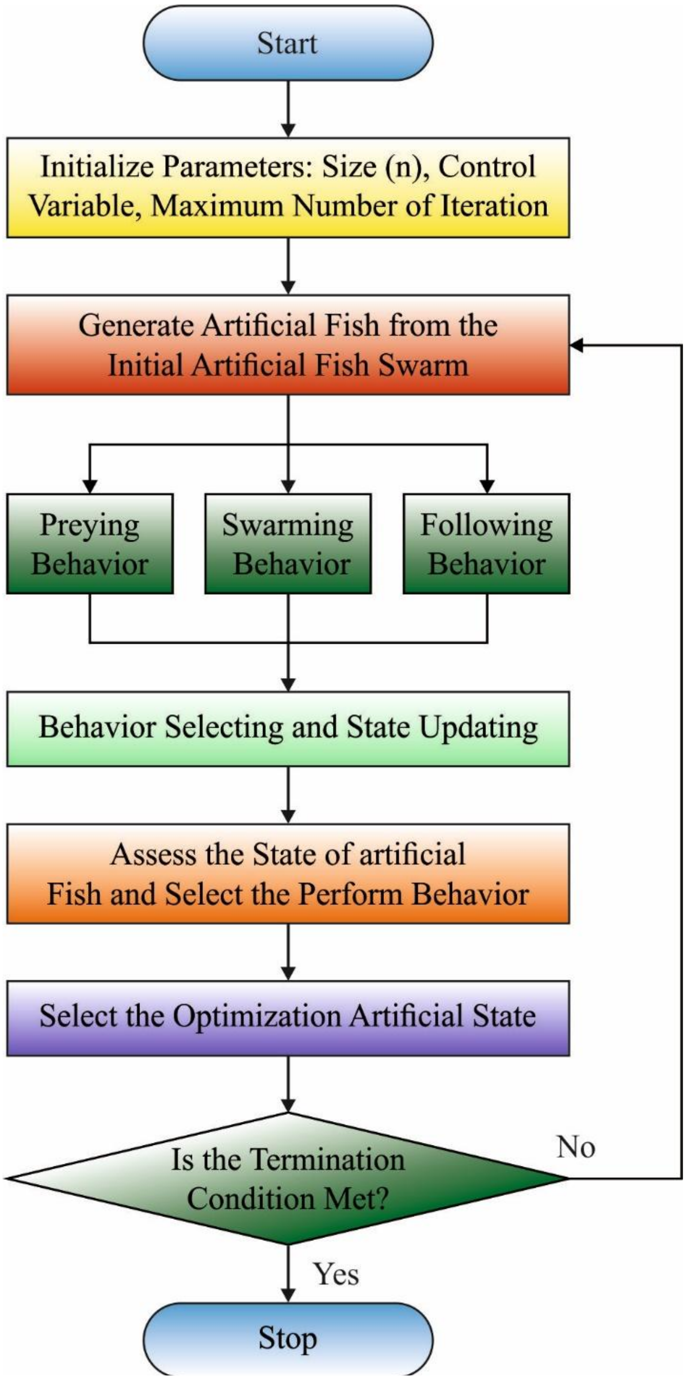

Fig. 2. Flowchart of AFSA

Swarm

In the swarming procedure, the fish has the natural capability to share food and prevent any distraction which can be confronted. Assume that the present state of the artificial fish is provided by X_j, and the overall amount of other fishes in its vision domain is represented as n. Currently, if $n_f = 0$, this must include that the visual domain of the provided artificial fish is empty, so it is time to execute praying [23]. But, when $n_f \geq 0$, this implies that there are other companion fishes existing in its vision domain, and it should begin seeking the central location X_c (viz., center among the current fishes) of its companion based on Eq. (4).

$$X_{ck} = \frac{\left(\sum_{j=1}^{n_f} x_{jk}\right)}{n_f}, \tag{4}$$

In which X_c signifies the central location of the artificial fish amongst them, X_{ck} provides the kth component of X_c, and X_{jk} signifies the kth component of the vector of jth companion $j = (1, 2, \ldots, n)$. The computation of the food concentration of the artificial fish at the central location, provided by Y_c, indicates the objective function with the limitation of $Y_c \frac{n_f}{Y_i} > 1$. When the central location is safer and less congested, the artificial fish should move to this location by Eq. (5); otherwise, praying is implemented.

$$x_{i-next-k} = x_{i\to k} + \frac{x_{ck} - x_{ik}}{\|X_c - X_i\|} * random(step). \tag{5}$$

Chasing

In an artificial fish swarm, once fishes are seeking food, neighboring partners have the natural capacity to reach and trace food rapidly, assume that X_j indicates the present state of the artificial fish and n represent the overall amount of companions in its visual domain. Here, when $n_f = 0$, it demonstrates that the visual domain of the artificial fish is empty; hence, praying must be executed. But, when $n_f \geq 1$, it implies that few companions even exists in its visual domain; thus, it must find and search for a companion with a minimal value of the respective function $X_{\max}$. Next, the limitation is verified, viz., $Y_{\max} \frac{n_f}{Y_i} > 1$, when it is valid, it implies that the fitness values of the respective companion are smaller and it isn't congested; therefore, Eq. (6) is executed; or else, praying is executed.

$$x_{i-next-k} = x_{i\to k} + \frac{x_{\max,k} - x_{ik}}{||X_{\max} - X_i\|} * random\ (step). \tag{6}$$

In which $x_{\max,k}$ provides the kth component of state vector $X_{\max}$.

Originally, Tizhoosh improved the evolutionary trajectory by presenting of oppositional based learning (OBL) approach [24]. When $(x_1, x_2, \ldots, x_D)$, is consider as $x_i \in [\alpha_i^{lb}, \beta_i^{ub}]$ and x_i represent real number in a D-dimension space, hence its opposite number, x^o, is determined by:

$$x_i^o = \alpha_i^{lb} + \beta_i^{ub} - x_i (i = 1,2,3, \ldots, D) \tag{7}$$

The above description of the opposite point can be determined according to the relationships among points from the search space without taking into account its target values. If x and their opposite, x^o, in distinct dimension space.

AFSA is started by the early population and focuses on enhancing them towards optimum solution. The method of searching determines while some predetermined conditions are ensured. The procedure is started by arbitrary guesses from the lack of a priori information regarding the solutions. This study could be augmented by starting with closer that is fitter solutions by opposite solution. By taking into account OBL approach, the fitter one (guess or opposite guess) might be elected as an early solution. The fundamental concept of probability, half of the time value, a guess is far from the solution than its opposite guess. Hence, the procedure starts with the nearer of the 2 guesses. The duplicate process could be approached to the earlier solution as well as continue to every solution in the present population.

Originally, a Quasi-Oppositional (QO) based learning model for attaining the applicant solutions by the present population in addition to its QO simultaneously. Since it appears to be AFSA method which offers a quasi-opposite number i.e., generally nearer by an arbitrary value to the solution. Additionally, it has been demonstrated that a QO number is generally nearer by an opposite number to the solution [25]. During this work, the researchers have attempted to employ the QO method for pre-processing which includes generation jumping and population initialization. Since it is determined in OBL regarding the opposite of real number in D-dimension space, for real numbers, such as $x(x_1, x_2, \dots, x_D)$, subjected to $x_i \in [\alpha_i^{lb}, \beta_i^{ub}]$, its quasi-opposite number, x^{qo}, is presented by:

$$x_i^{qo} = rand\left(\frac{\alpha_i^{lb} + \beta_i^{ub}}{2}, x_i^o\right)(i = 1,2,3, \dots, D) \tag{8}$$

As abovementioned, it is feasible to achieve appropriate applicant solution QO-based population initiation might attain fitter candidate solution as the simultaneous deliberation of the arbitrarily created early position and their QO position enhances the quality of the early population and accelerates the searching procedure by examining the strong region of the search space. The QO-based population initiation can be defined as follows:

Algorithm 1: QOBL based Population Initialization
Create primary random population: x For $i = 1: N_{pop}$ For $j = 1: D_p$ $x^0(i,j) = \alpha^{lb}(1,j) + \beta^{\iota\ell b}(1,j) - x(i,j)$ $C(i,j) = \alpha^{lb}(1,j) + \beta^{ub}(1,j)/2$ if $(x(i,j) < C(i,j))$ $x^{q0}(i,j) = C(i,j) + (x^0(i,j) - C(i,j)) \times\ rand$ else $x^{q0}(i,j) = x^0(i,j) + (C(i,j) - x^0(i,j)) \times\ rand$ end end end

The optimization process might be forced to skip on the basis of jumping rate, J_r, to novel applicant solutions i.e., very suitable when compared to the existing one. Afterward generating a new population on the basis of on Jr, the QO population can be evaluated, and the more appropriate population gets categorized in the union of present and QO population depends on applicant solutions. During this work, the time varying jumping rate has been evaluated by:

$$J_r = \frac{\Delta J_r \times NFR}{NFR^{\max}} \tag{9}$$

whereas $\triangle J_r = J_r^{\max} - J_r^{\min}$ and NFR represents the amount of function recall at the present iterations. During this study, the jumping rate is regarded as $J_r \in [0,0.4]$. Thus, the CC of QO-based generation jumping has been demonstrated below.

Algorithm 2: QOBL based Jumping Rate generation

Compute jumping rate: J_r
If (rand $< J_r$)
For $i = 1: N_{pop}$
For $j = 1: D_p$
$x^0(i,j) = \alpha^{lb}(1,j) + \beta^{ub}(1,j) - x(i,j)$
$C(i,j) = \alpha^{lb}(1,j) + \beta^{ub}(1,j)/2$
if $(x(i,j) < C(i,j))$
$x^{q0}(i,j) = C(i,j) + (x^0(i,j) - C(i,j)) \times rand$
else
$x^{q0}(i,j) = x^0(i,j) + (C(i,j) - x^0(i,j)) \times rand$
end
end
end
end

The QOAFSA-MRP technique develops a fitness value of all solutions or routes amongst the CH as well as BS. The purpose of QOAFSA-MRP based routing approach is for determining the route with less energy consumption and minimum distance. The fitness function (FF) has been regarded as the minimize function and has been demonstrated as:

$$F_i = \min\{\mathrm{RE}_i \times DIST_i\} \tag{10}$$

where, 'F_i' refers the fitness of ith populations, 'RE_i' signifies the energy required from the ith population and '$DIST_i$' implies the entire distance of ith route/population. In QOAFSA-MRP, the presented route amongst the CH as well as BS has been modified as initial population. In the initial stage, the CH develops a broadcast and another CH/BS develops the target. So, the probable route in CH to BS has been determined as:

$$Sol = P_i, \qquad i = 1,2,\cdots,N. \tag{11}$$

where 'Sol' refers the primary population set, 'P_i' describes the ith route in CH to BS, and 'N' represents the route count. The route includes distance and entire energy as provided under.

$$P = \{RE, DIST\} \tag{12}$$

where 'RE' refers the node residual energy from the route and 'DIST' stands for the entire distance of route. The standard deviation (SD) to RE (σ_{RE}) has been utilized for measuring the value of uniform load dispersal among sensors as determined under.

$$RE = f_1 = \sigma_{RE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left\{\mu_{RE} - e\left(node_j\right)\right\}^2} \tag{13}$$

$$\mu_{RE} = \frac{1}{n}\sum_{i=1}^{n} E\,(node_i)$$

Afterward, the distance in the CH to BS has been defined as the entire Euclidean distance amongst all CHs from the route has been demonstrated in Eq. (14).

$$DIST = \sum_{i}^{n-1}\sqrt{\left(CH_i(x) - CH_{i+1}(x)\right) + \left(CH_i(y) - CH_{i+1}(y)\right)} \tag{14}$$

where$CH_i(x)$ and $CH_i(y)$ indicates the x and y coordinates of i^{th} CH from the route correspondingly.

4. Performance Validation

The performance validation of the QOAFSA technique is carried out and the results are investigated interms of different measures. Table 1 illustrates a brief comparative analysis of the QOAFSA with existing techniques interms of different measures.

Table 1 Result Analysis of Existing with Proposed QOAFSA Method in terms of Different Measures

Average Lifetime of Cluster Head vs Velocity				
Velocity (m/s)	**CACONET**	**ICMFO**	**FA-OLSR**	**QOAFSA**
10	121	153	174	194
20	127	132	162	202
30	131	136	160	190
40	119	126	156	200
50	109	120	148	192
Average Lifetime of Cluster Member vs Velocity				
Velocity (m/s)	**CACONET**	**ICMFO**	**FA-OLSR**	**QOAFSA**
10	128	165	196	238
20	123	174	201	248
30	112	181	198	234
40	102	156	194	246
50	98	173	186	255
Average Cluster Count versus Velocity				
Velocity (m/s)	**CACONET**	**ICMFO**	**FA-OLSR**	**QOAFSA**
10	8.80	8.60	6.50	4.10
20	8.90	8.80	6.80	4.30
30	8.60	8.50	6.70	4.40
40	8.40	8.90	6.50	4.60
50	9.30	9.10	6.90	4.70

Fig. 3 depicts the average lifetime of CH (ALCH) analysis of the QOAFSA with other techniques under varying rates of velocity. The figure has shown that the QOAFSA technique has gained an increased ALCH compared to others. For instance, with the velocity of 10m/s, the QOAFSA technique has obtained an increased ALCH of 194 whereas the CACONET, ICMFO, and FA-OLSR techniques have resulted in a reduced ALCH of 121, 153, and 174 respectively. In line with, the velocity of 30m/s, the QOAFSA approach has gained a higher ALCH of 190 whereas the CACONET, ICMFO, and FA-OLSR manners have resulted in a lower ALCH of 131, 136, and 160 correspondingly. Moreover, with the velocity of 50m/s, the QOAFSA technique has obtained a maximum ALCH of 192 whereas the CACONET, ICMFO, and FA-OLSR methodologies have resulted in a lower ALCH of 109, 120, and 148 correspondingly.

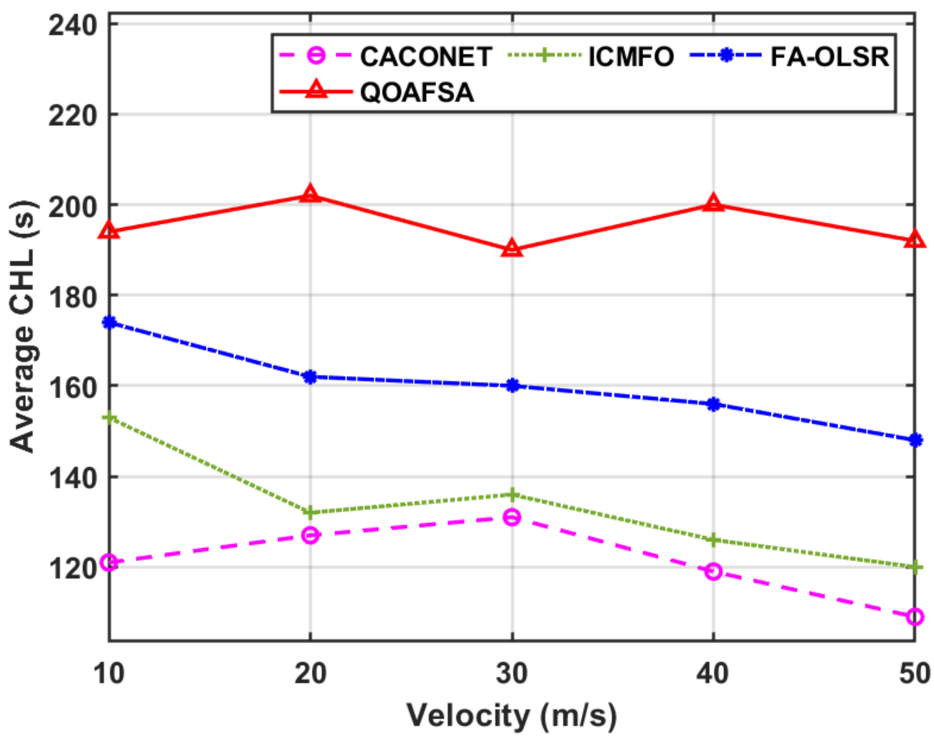

Fig. 3. ALCH analysis of QOAFSA model under varying velocity

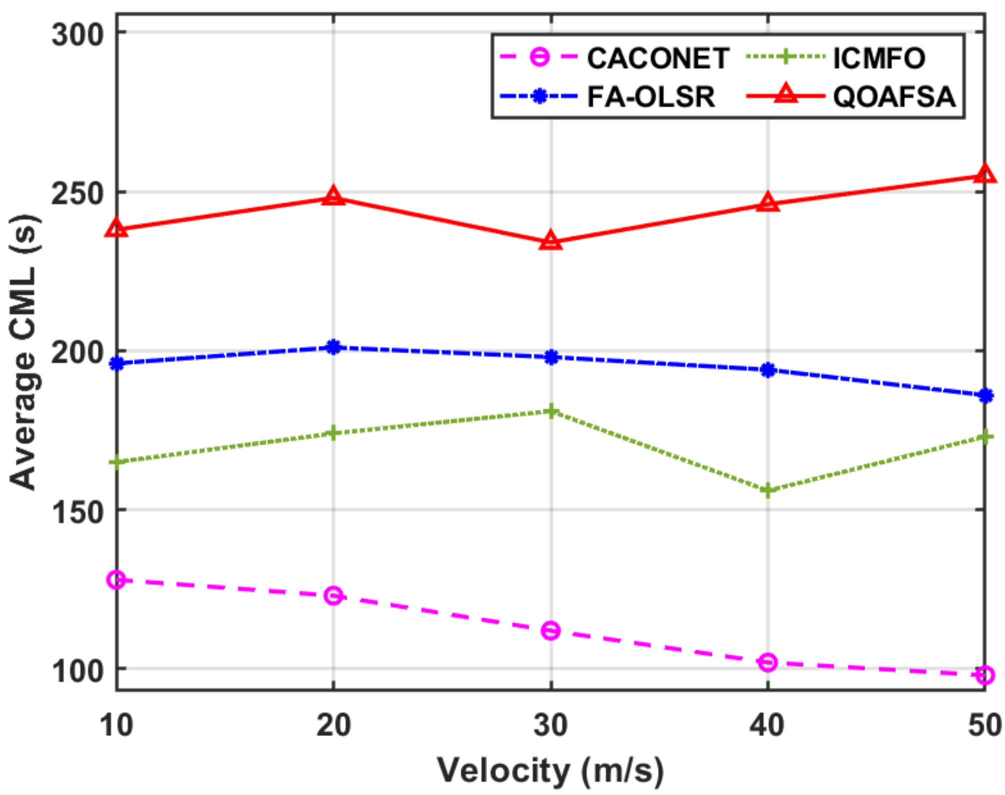

Fig. 4. ALCM analysis of QOAFSA model under varying velocity

Fig. 4 showcases the average lifetime of CM (ALCM) analysis of the QOAFSA with other approaches under varying rates of velocity. The figure exhibited that the QOAFSA system has attained a superior ALCM compared to others. For instance, with the velocity of 10m/s, the QOAFSA manner has attained an enhanced ALCM of 238 whereas the CACONET, ICMFO, and FA-OLSR systems have resulted in a reduced ALCM of 128, 165, and 196 correspondingly. Followed by, with the velocity of 30m/s, the QOAFSA technique has achieved a maximal ALCM of 234 whereas the CACONET, ICMFO, and FA-OLSR techniques have resulted in a reduced ALCM of 112, 181, and 198 respectively. Finally, with the velocity of 50m/s, the QOAFSA method has reached a superior ALCM of 255 whereas the CACONET, ICMFO, and FA-OLSR algorithms have resulted in a reduced ALCM of 98, 173, and 186 correspondingly.

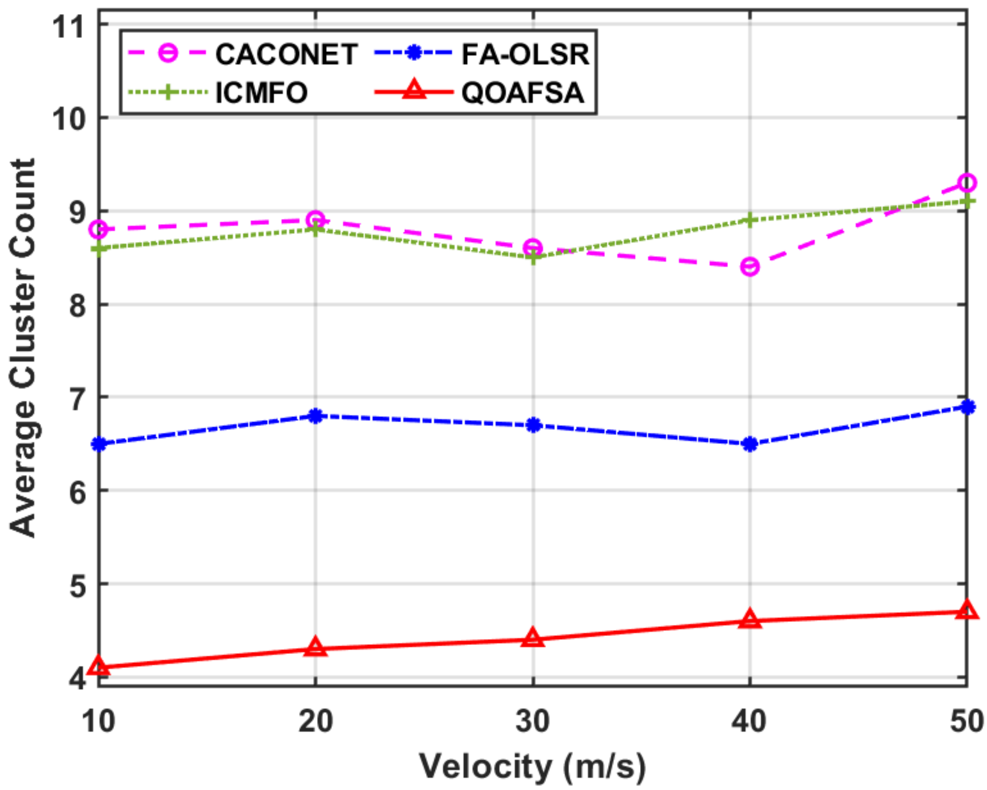

Fig. 5. ACC analysis of QOAFSA model under varying velocity

A comparative average cluster count (ACC) analysis of the QOAFSA technique takes place in Fig. 5. The results reported that the QOAFSA technique has gained effective outcomes with the lower ACC. For instance, with the velocity of 10m/s, the QOAFSA technique has attained a minimal ACC of 4.10 whereas the CACONET, ICMFO, and FA-OLSR techniques have accomplished an increased ACC of 8.80, 8.60, and 6.50 respectively. In the meantime, with the velocity of 30m/s, the QOAFSA method has gained a lesser ACC of 4.40 whereas the CACONET, ICMFO, and FA-OLSR methods have accomplished an improved ACC of 8.60, 8.50, and 6.70 respectively. Eventually, with the velocity of 50m/s, the QOAFSA technique has reached a lower ACC of 4.70 whereas the CACONET, ICMFO, and FA-OLSR schemes have accomplished to a higher ACC of 9.30, 9.10, and 6.90 correspondingly.

Table 2 examines a detailed comparative analysis of the QOAFSA with existing manners interms of distinct measures.

Table 2 Result Analysis of Existing with Proposed Method in terms of EC, Delay, and PDR

Average Energy Consumption versus Velocity				
Velocity (m/s)	**CACONET**	**ICMFO**	**FA-OLSR**	**QOAFSA**
10	17.00	15.00	10.89	8.86
20	18.00	15.60	10.73	8.61
30	19.00	16.80	12.71	8.89
40	20.00	17.30	12.88	9.02
50	22.00	17.80	12.65	9.12
Average Delay (ms) vs Number of Vehicles				
No. of Vehicles	**CACONET**	**ICMFO**	**FA-OLSR**	**QOAFSA**
65	4532	3274	2773	1315
85	4281	2984	1948	1195
105	4073	2846	1846	1092
125	3937	2482	1753	1030
145	3872	2371	1347	819
165	3527	2295	1298	655
185	3219	2180	1108	547
Average Packet Delivery Ratio vs Number of Vehicles				
No. of Vehicles	**CACONET**	**ICMFO**	**FA-OLSR**	**QOAFSA**
65	0.71	0.73	0.76	0.88
85	0.69	0.72	0.78	0.92
105	0.67	0.70	0.81	0.93
125	0.66	0.67	0.83	0.95
145	0.64	0.65	0.86	0.96
165	0.62	0.61	0.88	0.97
185	0.59	0.58	0.92	0.98

A comparison average energy consumption (AEC) analysis of the QOAFSA approach takes place in Fig. 6. The results reported that the QOAFSA technique has gained effective outcomes with the minimum AEC. For instance, with the velocity of 10m/s, the QOAFSA algorithm has attained a minimal AEC of 8.86 whereas the CACONET, ICMFO, and FA-OLSR techniques have accomplished a maximum AEC of 17.00, 15.00, and 10.89 respectively. Meanwhile, with the velocity of 30m/s, the QOAFSA manner has attained a minimal AEC of 8.89 whereas the CACONET, ICMFO, and FA-OLSR systems have accomplished a higher AEC of 19.00, 16.80, and 12.71 respectively. At last, with the velocity of 50m/s, the QOAFSA approach has attained a minimal AEC of 9.12 whereas the

CACONET, ICMFO, and FA-OLSR methodologies have accomplished an enhanced AEC of 22.00, 17.80, and 12.65 correspondingly.

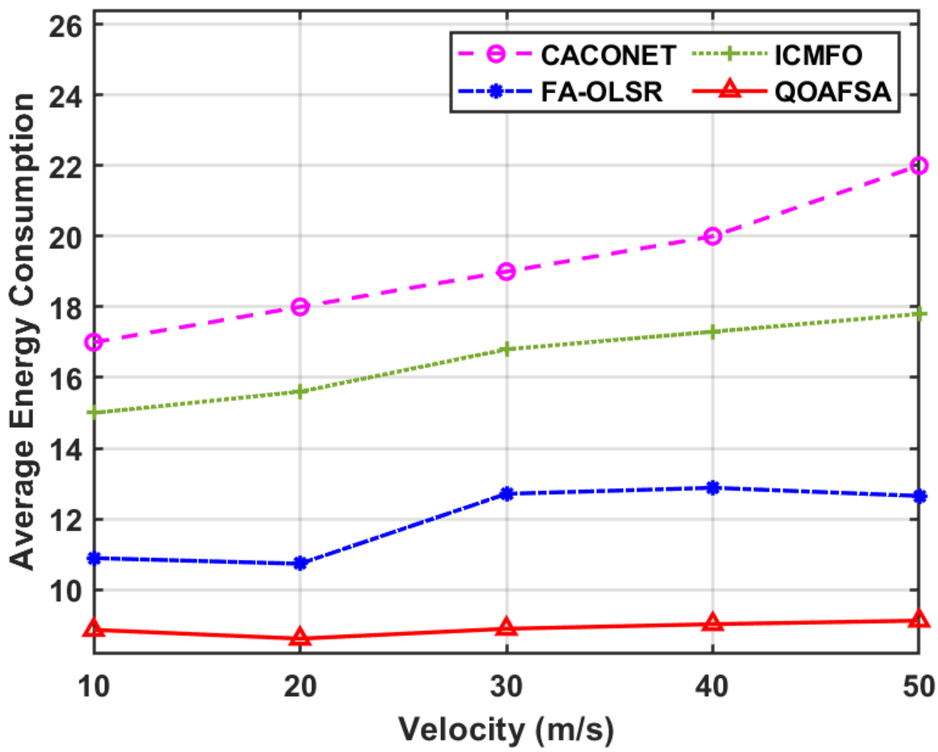

Fig. 6. AEC analysis of QOAFSA model under varying velocity

A comparative average delay (AD) analysis of the QOAFSA technique takes place in Fig. 7. The results reported that the QOAFSA technique has gained effective outcomes with the lower AD. For instance, with vehicles of 65, the QOAFSA technique has obtained a lesser AD of 1315ms whereas the CACONET, ICMFO, and FA-OLSR techniques have accomplished an improved AD of 4532ms, 3274ms, and 2773ms respectively. At the same time, with the vehicles of 125, the QOAFSA system has reached a minimal AD of 1030ms whereas the CACONET, ICMFO, and FA-OLSR techniques have accomplished an increased AD of 3937ms, 2482ms, and 1753ms respectively. Lastly, with the vehicles of 185, the QOAFSA algorithm has attained a minimal AD of 547ms whereas the CACONET, ICMFO, and FA-OLSR methods have accomplished a maximal AD of 3219ms, 2180ms, and 1108ms respectively.

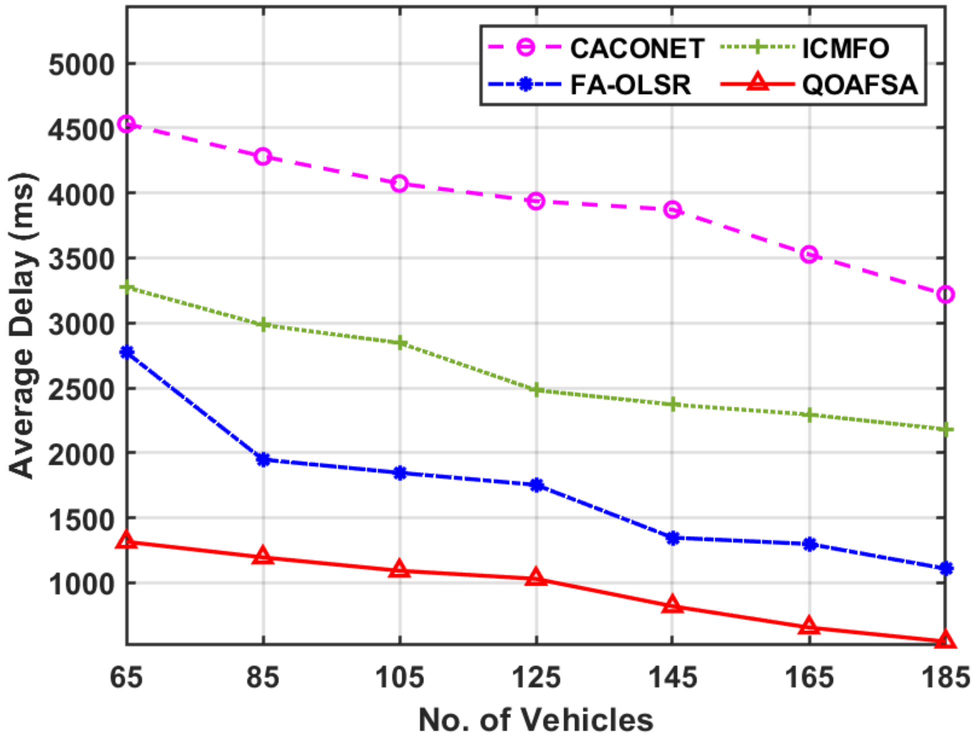

Fig. 7. Average delay analysis of QOAFSA model under the count of vehicles

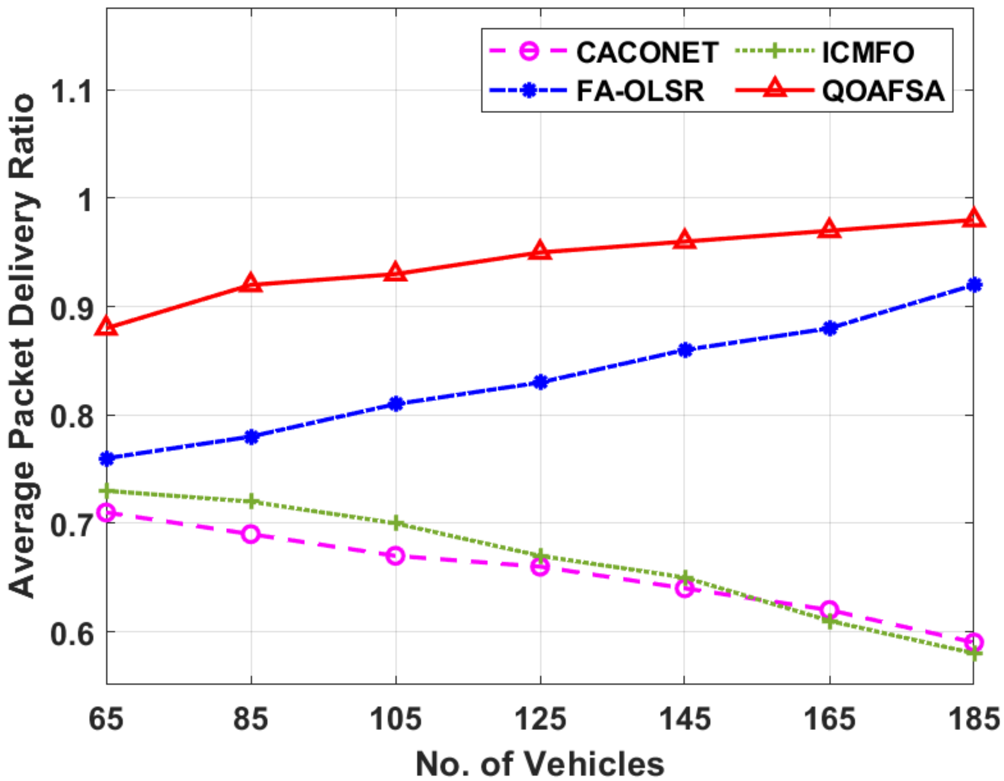

Fig. 8. APDR analysis of QOAFSA model under the count of vehicles

Finally, Fig. 8 depicts the average packet delivery ratio(APDR) analysis of the QOAFSA with other techniques under varying rates of vehicles. The figure has shown that the QOAFSA approach has gained an increased APDR compared to others. For instance, with vehicle 65, the QOAFSA technique has reached an increased APDR of 0.88 whereas the

CACONET, ICMFO, and FA-OLSR techniques have resulted in a reduced APDR of 0.71, 0.73, and 0.76 respectively. Likewise, with the vehicles of 125, the QOAFSA technique has obtained an increased APDR of 0.95 whereas the CACONET, ICMFO, and FA-OLSR techniques have resulted inthe least APDR of 0.66, 0.67, and 0.83 respectively. Finally, with the vehicles of 50, the QOAFSA manner has obtained a superior APDR of 0.98 whereas the CACONET, ICMFO, and FA-OLSR techniques have resulted in a decreased APDR of 0.59, 0.58, and 0.92 respectively. From these result analysis, it is ensured that the QOAFSA-MRP technique can be employed for optimal route selection in VANET.

5. Conclusion

In this study, a novel QOAFSA-MRP technique is derived for multi-hop routing in VANET. The proposed QOAFSA-MRP technique initially executes the WCS to choose the CHs proficiently. Followed by, the QOAFSA technique is employed to effectively select the optimal set of routes to destination. The QOAFSA technique involves the integration of QOBL with traditional AFSA to enhance the convergence rate. Furthermore, the QOAFSA-MRP technique derives a fitness function involving diverse network parameters for effective selection of routes to destination. For examining the improved outcomes of the QOAFSA-MRP technique, widespreadexperimentation takes place and the results are inspected under varying aspects. The obtained experimental values pointed out the supremacy of the QOAFSA-MRP technique over the other techniques. In future, trust aware routing protocols can be derived to accomplish security in VANET.

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