Mobile Networks and Applications
https://doi.org/10.1007/s11036-019-01257-z

A Reputation based Weighted Clustering Protocol in VANET: A Multi-objective Firefly Approach

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Abstract
Vehicular Ad hoc NETworks (VANETs) possess a dominant role in the development of Intelligent Transport Systems (ITS). VANETs, due to the rapid mobility of vehicles are a highly dynamic network. In order to make the network topology suitable for effective communication, clustering algorithms are widely used. Clustering algorithms enable VANET to efficiently handle the changing topology for Medium Access Control (MAC), routing and several other applications. In this work we put forward a Reputation based Weighted Clustering protocol (RWCP) for VANETs. The RWCP is framed by taking the direction of vehicles, position, velocity, number of nearby vehicles, lane ID, and the reputation of each node into consideration for stabilizing the VANET topology. On the other hand, dealing with diverse control parameters of RWCP makes optimizing a challenging task. The work employs a multi-objective problem which takes the RWCP's parameters as the input and aims at providing enhanced cluster lifetime, Improved packet delivery ratio and reduced cluster overhead. Multi Objective Firefly Algorithm (MOFA), an evolutionary approach is used for optimizing the RWCP's parameters. Simulations were done using the TETCOS NetSim simulator and MOEA framework for optimization. The results are evaluated with similar evolutionary optimization techniques. Experiments were conducted with realistic maps from OpenStreet Maps and its results were compared with other multi-objective optimization techniques: Multi-objective Particle Swarm Optimization (MOPSO) and Comprehensive learning Particle Swarm Optimization (CL-PSO). The investigation proposes that, the proposed methodology performs well concerning the Mean Cluster Lifetime, Packet Delivery Ratio and Control Packer Overhead.

Keywords VANET · Clustering · Multi-objective optimization · Pareto front · MOPSO · MOFA

1 Introduction

Vehicular Ad-hoc Network is a group of Ad-hoc wireless network with functionalities like Mobile Ad-hoc Network (MANET). It is mainly utilized to enhance the safety of vehicles, provide traffic management, and infotainment in vehicles. VANET and MANET have their share of differences; VANET Topology is dynamic in light of the fact that the speed of vehicles is high and is predictable to a degree with the assistance of GPS and the course of movement. On the other hand, MANET topology cannot be predicted and also has the constraint of energy in the nodes [1]. Vehicle to Vehicle Communication (V2V) empowers every vehicle to send out alerts whenever a critical event is anticipated. The alert messages can be through some sounds, or light indicators in the dashboard or vibrations in the steering wheel. Federal Communication Commission (FCC) has confined a remote convention called Dedicated Short-Range Communications (DSRC) [2]. DSRC is a wireless protocol which is developed for working in high dynamic networks which requires rapid link establishment and to reduce latency. In the United States FCC has designated 5.9 GHz for DSRC approach to endorse public and commercial utilization for V2V and Vehicle to Infrastructure (V2I) communication. It works in the frequency band of 5.9 Ghz with a total bandwidth of 75 MHz. 10 Mhz is allotted to channel for a total of 7 channels. The 7 channels are further categorized towards 1 Control Channel (CCH) and 6 Service Channels (SCH). CCH is assigned for high priority messages and the SCH is dedicated for all other transmissions.

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Published online: 22 April 2019

Clustering is an important unsupervised classification technique where a set of patterns in a multi-dimensional space are formed in groups based on some similarity parameters [3]. In a network like VANET, it is vital that all the vehicles broadcast their connectivity information to neighboring nodes periodically. A clustering structure within the network not only aids in broadcasting their connectivity information but also reduces the communication overhead [4]. Besides this the clustering approach also supports the coordination of CCH [5], routing [6], and security [7]. Nevertheless, clustering protocol faces the issue of maintaining the cluster structure and ensuring stable clusters without any overhead. For this reason, the article proposes a Reputation based Weighted Clustering Protocol which utilizes evolutionary advancement to solve the issue of forming stable clusters.

The firefly algorithm (FA) is a recent nature inspired approach [8], which has been used for addressing nonlinear optimization problems. The approach follows the conduct of the glowworms (fireflies). Fireflies have the tendency to get attracted to each other and form groups based on certain measures. Algorithms established on nature or evolution have been proven to significantly solve several optimization problems. In this study Firefly Algorithm as found by Xin she Yang [8] is applied to Reputation based Weighted Clustering Algorithm to optimize its parameters. The main contributions in the paper are 1) The concept of Reputation employed to clustering Protocol established with Weighted Clustering Algorithm [9] for VANETs. 2) For optimizing and fine tuning, the RWCP configuration, a strategy using Multi-objective Firefly algorithm is proposed. 3) Realistic VANET mobility models are taken from the city of Chennai (India), to validate the proposed strategy.

The article is formed as given here. Related work is conferred in Section 2. The proposed system about RWCP is given in Section 3 and the optimizing parameters and Performance Criteria are exhibited. Section 5 talks about the MOFA approach for RWCP optimization followed by Simulation results and validation in Section 6. Conclusion and Future work in section 7.

2 Related work

From the literature study done for this article, it is observed that several clustering protocols mainly focus on MANETs and its energy issues. However, there are only few approaches specifically for VANETs. Most of the protocols focus on the lane, highway ID, velocity as the basis for clustering, but to our knowledge none of the protocols takes the reputation of a node to form clusters along with velocity, direction, speed and lane.

In [10] the authors have managed to obtain the highway IDs and use it for forming stable clusters. The authors have also used Non-dominated Sorting Genetic Algorithm II (NSGA-II) for optimizing the Adaptive Weighted Clustering protocol (AWCP) which uses the highway IDs to form stable clusters. The article also has a comparison with Multi-objective Differential Evolution (MODE) and Multi-Objective Particle Swarm Optimization (MOPSO) which are frequently utilized in optimizing transmission in ad hoc networks. [11] utilizes the evolutionary capability of Ant Colony Optimization (ACO) to propose an algorithm to improve the quantity of clusters shaped. It applies the natural behavior of ants which form groups to look for the best solution. The proposed approach is computationally inexpensive, and best suited for scenarios where exhaustive search is required for identifying the best solution. Authors in [12] have determined a Multi-Head Clustering Algorithm which utilizes master slave strategy for stable cluster formation and maintenance. Nonetheless, the methodology has dispensed that each vehicle in the bunch move a similar way. In [4], an algorithm for cluster heads election has been designed specifically for highways. The methodology presents another parameter called distinction metric which regroups vehicles going at fast in one cluster and vehicles at a lower speed in another cluster. Weighted Clustering Algorithm (WCA) was proposed in [13] which elects a node based a computed weight including speed, energy level, the neighbor count and their average distance. From all these clustering algorithms, it is apparent that the configuration parameter has a good amount of influence on the clusters formed. Accordingly, the improvement of configuration parameters like *Cluster_Size, Hello_Interval, Time_Out_Interval* for different versatility situations must be given utmost significance. Authors in [14, 15] have applied meta-heuristic algorithms to improve AODV protocol's QoS as well as File Transfer Protocol (FTP) in realistic VANET's. Meta-heuristic algorithms have found to solve broadcast scheduling problems in VANET as seen in [16, 17].

In this article, a Reputation based Weighted Clustering Protocol (RWCP) is proposed. The approach uses the number of times a node has converted into a Cluster Head (CH) as the reputation of each cluster. The greater number of times a node has become a CH, the higher its reputation and is most likely to get elected as a CH for a particular cluster. In addition to this the work also focusses on optimizing the algorithm by creating a multi-objective problem for clustering in VANETs where FA is used to discover optimal configuration parameters for the proposed clustering protocol (RWCP).

3 Reputation based weighted clustering protocol (RWCP)

RWCP is a progression of the WCA [13], which recognizes vehicles in groups dependent on their highway ID's and each nodes reputation. The proposed methodology is set up on the presumption that each vehicle in a VANET knows its highway ID, speed, time and direction. All of these parameters are obtained through the Global Positioning System (GPS) installed in the vehicles. Along with this the algorithm brings in the novelty of applying the concept of Reputation. Reputation is calculated by the number of times a vehicle has become a cluster head (CH). Greater the number of times a node has become a cluster head it is said to have a good reputation and has more chances of becoming CH and performing the task of CH effectively. The following sections talks about the Cluster Head election and Cluster Maintenance.

3.1 Cluster head election

At the beginning, all the vehicles are set in the Initial State (IS). For an effective clustering to happen among the vehicles, every vehicle alters its category to Cluster Head Candidate (CHC) and commences to communicate a HELLO message periodically for every interval mentioned in the *Hello_interval* variable. The broadcast message is sent to its One-Hop Neighbors (OHN) with its Reputation (Set to 0, if it has never become a CH and increments by 1 each time it becomes the CH), direction, position, and speed. On receiving the broadcast message from all OHN's each vehicle x calculates its weight W_x using (1). The formula for computing the weight function is based on WCA as mentioned in [13].

$$W_x = w_1 * D_x + w_2 * V_x - (w_3 * N_x) - (w_4 * R_x) \tag{1}$$

Where D_x is the computed mean distance amongst vehicle x and its OHN. v_x is the speed of the vehicle, and V_x is obtained by (2).

$$V_x = \left| v_x - \frac{\sum y \in OHN_x v_x}{N_x} \right| \tag{2}$$

The number of one-hop neighbors are denoted by N_x. The representing weight factors w_1, w_2, w_3, w_4 are presented as given in (3)

$$\sum_{x=1}^{4} w_x = 1 \tag{3}$$

For the CH selection algorithm, each vehicle x periodically broadcasts an *election_interval* comprising of the vehicles ID, CH-ID (ID of the CH, which is associated with a particular vehicle), Highway ID, Weight, reputation and direction. Once the vehicle receives a message from its OHN's it arranges the neighbors list according to its weights received in the message. The vehicle with least W_x will be selected as the CH and assigns its ID in the ID field of the broadcast message. The Cluster selection algorithm also alters the states from IS to Cluster Member (CM) or Cluster Gateway) of CH. An illustrative example of the proposed approach is given in Section 6.

The CH selection algorithm as denoted in Algorithm 1. The algorithm ends when every vehicle in the range either turn into a CH, CM or a Cluster Gateway (CG) and they are not allowed to take part in another CH selection process.

The CH selection algorithm starts when vehicle y sends an ITJ to vehicle x. Vehicle x then checks if y is within its transmission range and if it's with the same highway ID, which is broadcasted along with the ITJ message. If the vehicles are within its transmission range then it forms its OHN list, N_x as mentioned in lines 2–4. When the OHN is not empty and if the Initial state is CHC for the node then the average distance Dx, and Velocity V_x are found out. Now for all the nodes in OHN, W_x is calculated as seen in lines 7–10. The next condition to be checked is to find if there are any more space in the cluster to include this cluster member. Next the W_x values are correlated to identify the node with the minimum W_x is made the CH and the other nodes are given CM, or CG accordingly. The steps will be repeated until all the nodes in the cluster have any of CH, CM, or a CG state.

3.2 Cluster maintenance

Once CH is elected, the fundamental duty of CH is to maintain the cluster. Operations in a cluster maintenance includes enrolling in a cluster, exiting a cluster, and merging clusters. The major task of an efficient clustering algorithm is not to use the clustering algorithm often. In order to achieve that, the cluster maintenance operations have to be done meticulously.

Algorithm 1 Cluster Head Selection

1	IS_x ← CHC; OHN_x ← NULL; R_x ← 0
2	On receiving ITJ from vehicle y, vehicle x checks:
3	If y is within transmission range and with same highway ID then
4	Compute One-hop Neighbors list (OHN), N_x
5	Else
6	Do Nothing
7	While OHN_x != 0 AND IS_x == CHC do
8	Compute the Average Distance D_x with its OHN
9	Compute V_x
10	Calculate W_x for all nodes in OHN
11	If cluster_size > number of CM then
12	Vehicle x will send an RTJ to y
13	Compare W_x values of all the nodes
14	Select the node with the least W_x as CH and other nodes as CM, CG
15	$R_x = R_x + 1$
16	Repeat steps 2 – 15 every time an ITJ is received

3.2.1 Enrolling in a cluster

The CH at regular intervals of time broadcasts ITJ messages to its OHN. Once an IS or CHC vehicle obtains an ITJ, and if it wants to enroll in the cluster, it sends back a Request-To-Join (RTJ) notification which has ID of vehicle and highway, reputation, direction and speed. When the CH receives RTJ notification it investigates for the ID of the highway and its direction. If it matches with the CH, the CH sends an acknowledgement (ACK). Once the ACK reaches the vehicle in IS, it changes its state from IS to CM. While being a CM if any vehicle gets an ITJ from another CH and if it has same highway ID and direction the vehicle can become a CG.

3.2.2 Exiting a cluster

A vehicle forms part of a cluster until it keeps receiving ITJ from its CH. When a CM stops receiving ITJ message during the *CH_Timeout_Interval*, it perceives that connection is lost with CH and hence changes its status from CM to CHC. Every CH maintains a list of timestamps for PRE-MSG received from every CM, if the CH finds that the timestamp of PRE-MSG and the current time is greater than *CM_Timeout_Interval*. If the CH has no incoming RTJ from any of its CM then it understands that all the CM's have left the cluster and the CH changes its state to CHC. If a CH for some reason leaves the cluster without handing over to another CH then the reputation will be reduced by −1.

3.2.3 Uniting clusters

At the point when a gathering of clusters move with same Highway ID and same way, every one of its CH may get ITJ messages from one another. In this scenario the CH will check for the signal strength to be greater than the threshold value and only one of the CH's will take the responsibility of CH and the other CH's will become CM. The election of CH for the uniting clusters will be based on their weight Wx.

4 Optimizing RWCP parameters and performance standards

Parameter setting plays a vital role in every protocol's performance. This article mainly focusses on the selection of parameter setting for the RWCP. An optimization technique is proposed to identify the efficient QoS RWCP configuration. RWCP parameters are specified in the Table 1. The parameters are of continuous type except for *Cluster_Size*. The *Cluster_Size* is the upper limit for the number of vehicles the cluster can handle which is computed by the eq. (4)

$$Cluster\_Size < (Tr^{*}\ln)^{*}\frac{2}{(lv+sd)} \tag{4}$$

Table 1 RWCP Parameters

Parameter	Lower bound	Upper bound
Hello_Interval	0.5	15
Election_Interval	0.5	15
ITJ_Interval	1	15
PRE_Interval	1	15
CH_Timeout_Interval	2	45
CM_Timeout_Interval	3	45
Cluster_Size	1	$(Tr^{*}\ln)^{*}\frac{2}{(lv+sd)}$
Weight of Distance (w_1)	0	1
Weight of Velocity (w_2)	0	1 - w_2
Weight of Reputation (w_3)	0	1 - (w_1+ w_2)
Weight of OHN_x (w_4)	0	1 - (w_1+ w_2 + w_3)

Where Tr specifies the transmission range, ln is the number of lanes, lv mentions the standard length of vehicles. 3 m is assumed to be the standard lv. sd refers to the standard.

Mean Cluster Lifespan (MCL), Control Packet Overhead (CPO), Packet Delivery Ratio (PDR) are the parameters selected for assessing a given RWCP configuration. These parameters are some of the most critical and most utilized in the field of study [4]. MCL is the arithmetic mean of the time period. It is calculated as the time from which a vehicle is either a CH, CM, or a CG till it changes its state. CPO denotes RWCP control packets rate which is utilized to form and preserve the cluster structures. PDR signifies the proportion of the number of data packets that are rightly reaching their targets. The optimized solution should have maximum MCL, minimal

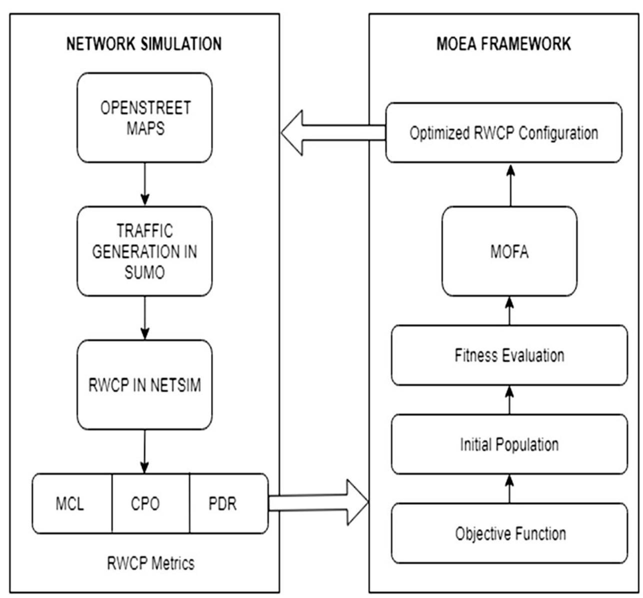

Fig. 1 Architecture for MOFA based optimization for RWCP optimization

CPO, and increased PDR. Owing to the contradictory nature of the objective functions and the large search space RWCP parameter tuning is treated as an NP-hard problem [18]. Therefore, RWCP parameter tuning is treated as a multi-objective problem and we have put forth an evolutionary approach to deal with the identified problem. We also propose an optimization tool which consists of a combination of MOFA and a NETSIM version 10 as the network simulator to figure out the optimal parameters of RWCP.

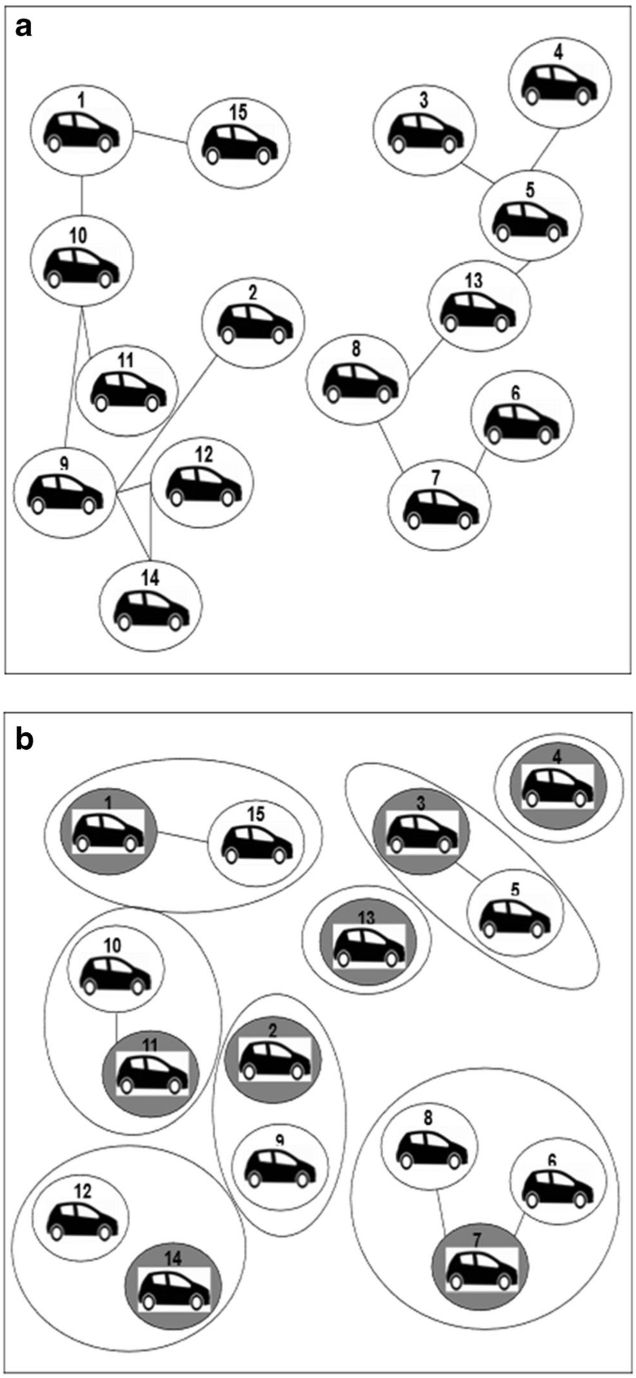

Fig. 2 **a** Initial setup of the assumed network. **b** Clustered nodes after employing RWCP

5 Multi-objective firefly algorithm (MOFA) approach for RWCP optimization

FA imitates the features of tropic firefly swarms and their twinkling behavior. FA has two vital assets which makes it better than other swarm intelligence algorithms. Local attractions and automatic regrouping are the exceptional traits of FA. As light intensity and distance are proportional, the attraction between the fireflies tend to be global or local based on the absorption coefficient [19]. This makes it visit every global and local modes. FA has the capability to sub-divide and regroup based on the neighboring attraction, this advantage of FA makes it more suitable for the clustering problem in this study [20]. To the best of our knowledge this is the first time MOFA has been used to optimize the RWCP parameters in Clustering of VANETs.

5.1 Overview of MOFA

Xin She Yang [20, 21] developed Firefly algorithm for continuous optimization, which was employed in various other fields such as structural optimization, image processing, computer networks etc. FA habits the three concepts as mentioned here a) Fireflies are considered to be of the same sex and each firefly will be attracted to other fireflies irrespective of their sexes. b) The fireflies get attracted towards by the brightness, the firefly with less brightness will move towards a firefly with high brightness. Brightness and distance are proportional. c) The objective function determines the brightness of a firefly.

The movement of firefly i towards a bright firefly j is influenced by eq. (5) which is obtained from [19].

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j^t - x_i^t\right) + \alpha_t \epsilon_i^t \tag{5}$$

Table 2 Clustering Parameters

S. No	Clustering Parameter	Cluster Information
1	*S_x*	Current State of Vehicle x
2	*Cluster_Size*	Size of the Cluster
3	*ITJ_Interval*	Time interim for CH to communicate its Invite-to-Join (ITJ) message
4	*PRE_Interval*	Time Duration for a CM to tell its existence to the CH
5	*CH_Timeout_ Interval*	A vehicle will choose itself as CH on the off chance that it didn't get any reaction to its ITJ messages

Where β is the attractiveness, α_t is the randomization parameter, and ϵ_i^t is a vector of random numbers from a uniform distribution. $r_{ij} = \|x_i - x_j\|$ is the cartesian distance of fireflies i and j at x_i and x_j. γ defines the variation of the attractiveness which is very crucial for FA to perform well.

5.2 Proposed approach

The proposed methodology is set up on a Java based Multi-objective Evolutionary Algorithm (MOEA) framework [22] and NETSIM network simulator version 10 [23]. The Architecture for the proposed approach is depicted in Fig. 1. Initially, OpenStreet Maps is used to get the real-world map data with GPS traces. It is then imported in SUMO to generate vehicle mobility. The generated mobility scenarios are given in NETSIM for implementing RWCP. Subsequently the trace files are generated and given to the MOEA framework for optimizing the parameters of RWCP. The MOEA framework computes the fitness functions and sorts the solutions based on the fitness functions. The process runs for generations until a stopping condition is met.

Algorithm 2 shows the algorithm for MOFA based RWCP optimization. The methodology starts by

Fig. 3 **a** Selection of Map area from OpenStreet. **b** Topology network of selected Map from SUMO

Table 3 Experimental Values for the 15-node network

Node id	OHN N_x	Velocity v_x	Velocity $\|V_x\|$	Distance D_x	Reputation R_x	Weight W_x
1	2	18	3	8	2	0.75
2	1	16	14	6	3	0.15
3	1	22	8	5	2	0.25
4	1	19	11	4	3	0.75
5	3	35	25	9	1	3.10
6	1	40	10	6	1	1.90
7	2	30	15	3	3	0.25
8	2	20	5	7	2	0.80
9	4	35	28	12	2	2.48
10	3	23	13	11	1	2.60
11	1	21	9	3	3	0.10
12	2	22	7	4	1	1.45
13	2	10	5	6	1	0.90
14	2	17	2	5	2	0.55
15	1	19	11	3	1	0.70

characterizing the target work and introducing a vector populace of n fireflies with uniform dissemination among the search space. The iterations start by deciding on the maximum number of generations and the fitness values of the functions are evaluated. Following that each firefly is compared with their intensities and are moved based on their attraction (lines 3–8). Then if no non-dominated solutions are found, a random walk is performed to identify the best solution. The solutions are communicated to the next set of iterations and once the maximum number of generations are reached, n non-dominated arrangements are acquired to approximate it to the optimized Pareto front (PF) (Lines 9–15).

In a minimization problem, solution vector $u = (u_1, \ldots\ldots, u_n)^T$ dominates another vector $v = (v_1, \ldots\ldots, v_n)^T$ if and only if $u_i \leq v_i \ \forall i \in \{1, \ldots\ldots, n\}$. The random walk is an important operator in MOFA. To improve on the efficiency of random walks we find the current best gt* by minimizing the compounded objective through the weighted sum as given in eq. 6

$$\varphi(x) = \sum_{k=1}^{K} w_k f_k \tag{6}$$

Here $w_k = \frac{p_k}{K}$, where p_k specifies the stochastic numbers picked from uniform distribution between 0 and 1. In order to get the non-dominated solution to sample diversely in the pareto front w_k should be chosen at random in every iteration and $\sum w_k = 1$. To satisfy this condition a regrading activity is executed subsequently after rendering K uniformly distributed numbers. On the off chance that a specific firefly isn't ruled by different fireflies, the firefly moves. The final optimized configurations are then given to the network simulator.

Algorithm 2 MOFA pseudocode for RWCP optimization

1 Define objective function $f_1(x)\ldots\ldots f_n(x)$
2 Population Initialization of n fireflies x_i (i=1,2,…..n)
3 ***While*** MaxGenerations
4   ***for*** i=1 to n
5   ***for*** j=1 to n
6   ***if*** $I_j < I_i$ ***then***
7   firefly i proceeds towards j using equation 5
8   ***end if***
9   ***if*** non-dominated solutions are **NOT** found ***then***
10   Random walks to find the best solution g^t_*
11   ***end if***
12   Update Solutions
13   ***end for***
14   ***end for***
15   Sort and locate the best estimation to the PF
16 ***end while***
17 Results and Visualization

6 Illustrative example

The initial and final stage of RWCP algorithm is presented in Figs. 2a and 2b. The clustering parameters are given in Table 2. The experiment was conducted for 15-node network with set transmission range and every node having the ability to broadcast and hear messages. A line/edge between two

Table 4 Simulation Parameters

Parameter	Value/Protocol
Number of nodes	20–100
Simulation area	750 m × 750 m
Packet Size	512 bytes
Transmission range	10 m - 180 m
Routing Protocol	AODV
Traffic type	Constant bit rate (CBR)
Mobility model	Random-way point
Vehicle speed	20 m/s
PHY/MAC Layer	IEEE 802.11p

vehicles signifies that the nodes are connected and are neighbors. One-hop neighbor (OHN) implies the total number of neighbors a node has. It is also referred to as the degree of the node. v_x is the velocity of each vehicle and $|V_x|$ is calculated as given in the eq. (2). D_x gives the distance between the vehicles. Rx gives the reputation of each vehicle. The reputation increases by 1 every time it becomes a CH. After all the values are determined, the weight W_x is computed with the eq. 1 and the values are tabulated in Table 3. For every vehicle the weights predetermined are $w1 = 0.05$, $w2 = 0.05$, $w3 = 0.7$, $w4 = 0.2$. The contribution of the weight factors can be fine-tuned based on the priorities given to the corresponding components. The weighing factor provides the tractability to adjust the effective contribution of each component. For example, if the reputation of a vehicle is more important, then the corresponding weight factor is made larger but the sum of the weights should be equal to 1. Figure 2a depicts the initial setup of the example. And Fig. 2b shows the final setup after the execution of RWCP algorithm along with its CH and connectivity. The strong vehicles are the distinguished CH's of the system. The node with least weight W_x is picked as the CH.

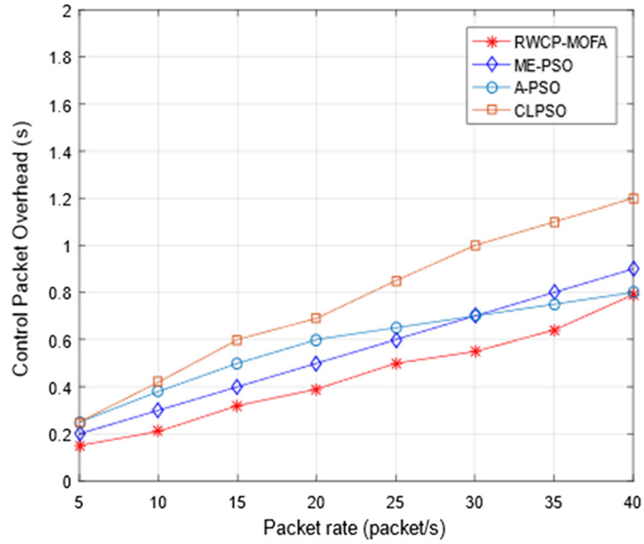

Fig. 5 Cluster Packet Overhead Comparison

7 Simulation results and performance evaluation

The simulation was conducted with the NETSIM simulator version 10 [22] and the MOEA framework [23] to optimize the RWCP parameters. The MOEA framework is a java-based framework specializing in Multi-objective Evolutionary Algorithms (MOEA) and the optimizing phase of the approach was carried out in it. The VANET simulation however was done

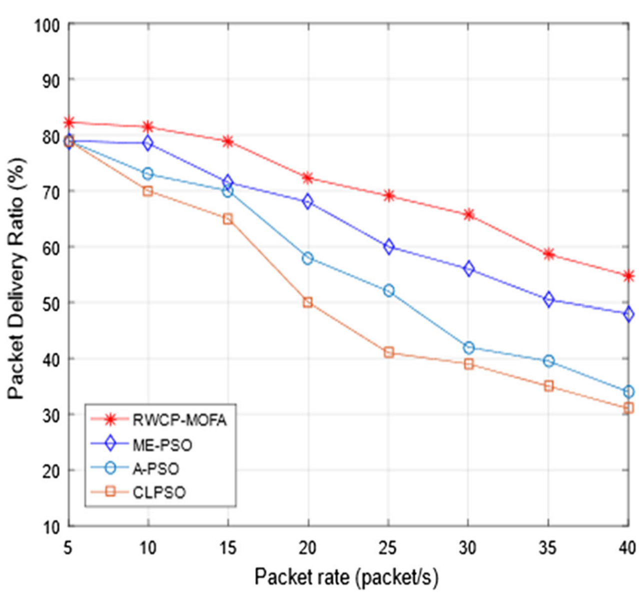

Fig. 4 Packet Delivery Ration Comparison

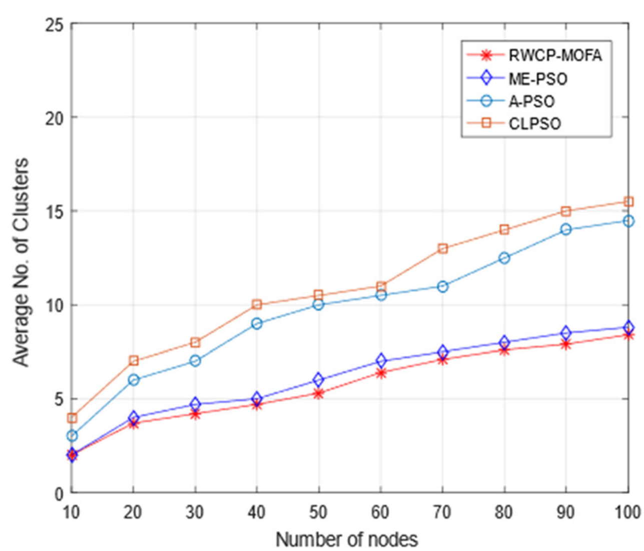

Fig. 6 Average number of Clusters Comparison

Table 5 Performance Comparison for the considered settings

Setting	Max No. of Vehicles	Total CBR	Transmission Range (m)	Algorithm	Avg No. of Clusters
Setting 1	20	5	30	CLPSO	15
				MOPSO	15
				RWCP-MOFA	13.2
Setting 2	30	10	30	CLPSO	25.1
				MOPSO	25.2
				RWCP-MOFA	23.8
Setting 3	50	15	30	CLPSO	34.5
				MOPSO	34.7
				RWCP-MOFA	33.6

in SUMO and NETSIM. All the experiments were done in a machine with Intel core i5 2.7Ghz with 8Gb of memory.

VANET scenarios was generated by selecting a digital map from OpenStreetMap (OSM). This map included lane directions, lane intersections, and traffic lights. Figure 3a shows Transport map of a metropolitan area in Chennai, India. It was exported from OpenStreetMap and altered utilizing Java OpenStreetMap Editor (JOSM). At that point SUMO was utilized to produce vehicular traffic situations for the considered guide as appeared in Fig. 3b. The traffic situations were created with parameters, for example, number of vehicles, the source and goal of vehicles, the begin time and end time. The traffic traces created were then utilized in NETSIM for reenactments. The Simulation parameter settings in NETSIM for the trials are appeared in the Table 4.

In this segment we depict the simulation results of the proposed methodology and results are benchmarked with two existing frameworks. Adaptive cluster formation in MANET using particle swarm optimization (A-PSO) [24] and clustering in MANET applying comprehensive learning particle swarm optimization (CLPSO) [25]. Figure 4 depicts the packet delivery ratio for RWCP-MOFA, A-PSO and CLPSO. It is clearly evident that RWCP-MOFA has increased PDR. This is due to the proposed approach which provides the additional stability of a good CH by incorporating the reputation factor into consideration. Reputation along with distance of neighbors, velocity, and OHN have certainly improved the lifetime of CHs. Since the CH doesn't move away from the cluster often the frequent need to re-clustering is also reduced. CPO with changing parcel rate for each of the three methodologies thought about is appeared in Fig. 5. It is seen from the Fig. 5 that RWCP-MOFA has a lower CPO than A-PSO and CLPSO. This is because the proposed approach focusses primarily on CH election which depends on the parameters specified in section 3. Thus, depending on the weight of the CH, a node gets affiliated with the one in its transmission range. Thus, the strong CHs will enable reduced rate of packets dropped and hence reduces the CPO in packet transmission. Figure 6 depicts the average number of clusters framed as the quantity of nodes increments. On observing the graph, RWCP-MOFA has a smaller number of clusters than A-PSO and CLPSO. The reason for this because the fitness function not only depends on the reputation of the CH but also on the distance between clusters, and vehicle velocity forming a more compact cluster with optimal number of vehicles for each CH.

The simulations considered three settings with varying number of vehicles in each setting as mentioned in the Table 5. The CBR values are varied according to the vehicle sizes and the transmission range is constantly set to 30 m. It is seen from the results that RWCP-MOFA forms a smaller number of clusters than MOPSO and CLPSO so that it can cover the entire network.

Table 6 demonstrates the mean and standard deviation of the best cost values got in running MOFA for 30 independent runs for the three settings taken under experimentation. We have also applied Wilcoxon Rank Sum Test to the distributions obtained from the results. The p value was set to 0.05 for the rank sum test. The results are shown in the Table 6. The test was conducted to the cost values of the algorithms for the three settings and resulted in values less than 0.05 proving that they are statistically different solutions. The optimal configuration found by MOFA is *Hello_Interval = 0.82, Election_Interval = 0.18, ITJ_Interval = 9.85, PRE_Interval = 11.42, CH_Timeout_Interval = 13.1,*

Table 6 Statistical analysis comparison for the assumed setting

VANET Setting	Mean (SD) of Best Cost	Wilcoxon test (*p* value)	Average MCL	Average CPO	Average PDR
Setting 1	1.517(1.02e-4)	5.58E-07	94.5 s	4.76%	96.70%
Setting 2	1.754(1.32e-4)	5.71E-07	84.8 s	7.89%	92.40%
Setting 3	1.891(1.60e-4)	5.89E-07	79.1 s	11.12%	86.30%

CM_Timeout_Interval = *14.5, Cluster_Size* = *50, W1* = *0.51, W2* = *0.28, W3* = *0.05, W4* = *0.16*. The obtained optimal configuration was then employed for the three settings and the QoS metrics results are displayed in Table 6 (columns 4,5, and 6).

To summarize, it is apparent from the results that the tuned RWCP configuration offers better efficiency for clustering in a VANET with the help of the three QoS metrics analyzed for the three settings considered. The solutions incurred by MOFA show increased packet delivery and Cluster Lifespan with reduced packet overhead.

8 Conclusion

In this article, we have covered the problem of clustering by introducing a reputation based weighted clustering protocol and tuning its parameters using a Firefly algorithm. The article characterizes an optimized approach dependent on Multi-objective Firefly Algorithm and the NETSIM simulator. Considering the high number accessible designs of RWCP and its conflicting objectives, a multi-objective optimization problem was defined. The findings of the proposed methodology are contrasted with other similar approaches such as Comprehensive learning Particle swarm optimization and Multi-objective Particle swarm optimization with scenarios acquired from the metropolitan city of Chennai, India. The obtained simulation results demonstrate that MOFA performs superior to the next two benchmarked approaches.

In addition, the proposed approach is also validated with a statistical test called as the Wilcoxon Rank sum test to prove the dissimilarities in the solutions obtained throughout the search space. As the number of vehicles increase the computation time required to perform the independent runs are prominently high. In future we plan on employing a parallel version of Multi-objective evolutionary algorithms with the help of multiple processors. This directly assists in catering to a large population with more generations and less computational time. As part of future improvements, we plan on conducting real tests by using vehicles and other infrastructures for validating our simulations.

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