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Optimized Node Clustering in VANETs by Using Meta-Heuristic Algorithms

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Abstract: In a vehicular ad-hoc network (VANET), the vehicles are the nodes, and these nodes communicate with each other. On the road, vehicles are continuously in motion, and it causes a dynamic change in the network topology. It is more challenging when there is a higher node density. These conditions create many difficulties for network scalability and optimal route-finding in VANETs. Clustering protocols are being used frequently to solve such type of problems. In this paper, we proposed the grasshoppers' optimization-based node clustering algorithm for VANETs (GOA) for optimal cluster head selection. The proposed algorithm reduced network overhead in unpredictable node density scenarios. To do so, different experiments were performed for comparative analysis of GOA with other state-of-the-art techniques like dragonfly algorithm, grey wolf optimizer (GWO), and ant colony optimization (ACO). Plentiful parameters, such as the number of clusters, network area, node density, and transmission range, were used in various experiments. The outcome of these results indicated that GOA outperformed existing methodologies. Lastly, the application of GOA in the flying ad-hoc network (FANET) domain was also proposed for next-generation networks.

Keywords: intelligent transportation system (ITS); vehicular ad-hoc networks (VANETs); grasshoppers' optimization; clustering; flying ad hoc network (FANET)

1. Introduction

Vehicular ad-hoc network (VANET) is a mobile ad-hoc network (MANET) in which communication is done among vehicles. VANET is an important component of the intelligent transportation system (ITS) [1], where vehicles contain wireless transceivers having different communication modes, namely, vehicle to vehicle (V2V) [2], vehicle to infrastructure (V2I) [3], and vehicle to anything (V2X) [4]. These communication modes utilize IEEE 802.11p [5] standard with dedicated short-range communications (DSRC) [6] and wireless access in vehicular environments (WAVE) [7] protocol stack. Node movement is more frequent in VANETs as compared to MANETs. Due to fast and random node mobility in VANETs, the network suffers from various problems, such as network availability, scalability, and overall network structural instability. It degrades network quality of service (QoS), and due to this reason, frequent communication failure occurs. As a solution to these issues, many protocols are introduced, and intelligent clustering protocols are among them.

Clustering a network is a process of dividing it into small logical groups. This process is based on different parameters, for example, internode distance and communication link capacity, to optimize

overall network performance. Small groups can be managed more effectively [8]. Various techniques are purely based on clustering. Clustering mechanisms also differ from each other because of different formation criteria [9]. These criteria can vary according to functionality and its domain of application. However, in the cluster network vehicles, nodes can act as cluster members (CM's) or can be elected as cluster heads (CH's). CM nodes are ordinary nodes, while CH's are responsible for inter-cluster and intra-cluster information forwarding in VANETs, as shown in Figure 1. Therefore, CH's are selected on the basis of their enhanced functionality to get optimized network performance. Therefore, CH's selection is essential to achieve reliable communication. As an example, CH's with dual wireless backbone networks (i.e., cellular or satellite interface) support are preferable instead of ordinary nodes [10], making the election of suitable CH a challenging task for VANETs. Due to this, optimal clustering in VANETs also belongs to a category of Non-Polynomial-hard problems. For these types of problems, near-optimal solutions are acceptable because perfect solutions are hard to obtain. To address these issues, many classical algorithms have been proposed in a similar domain but failed to obtain an ideal clustering solution.
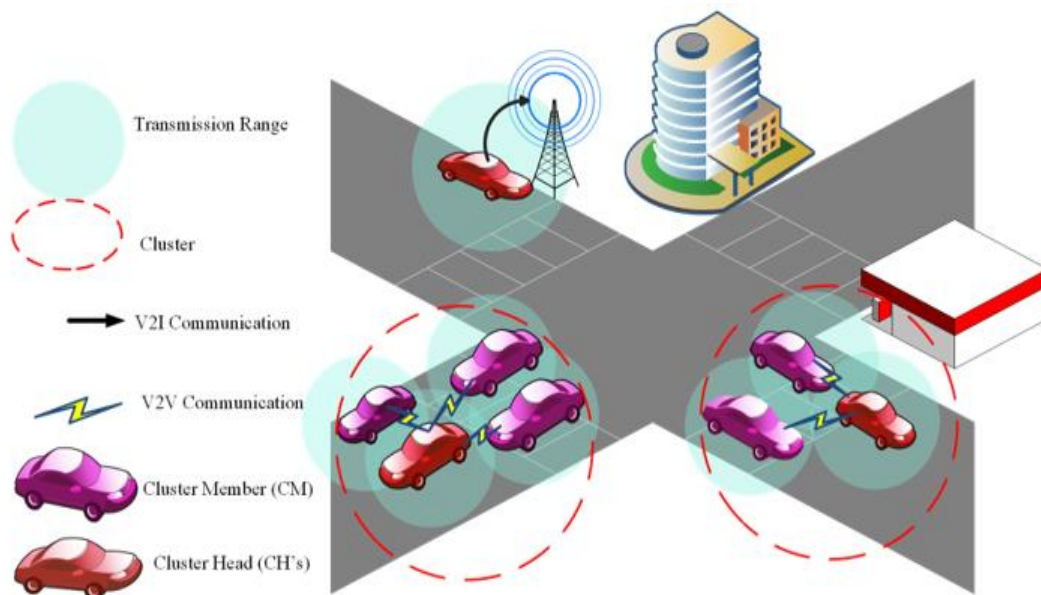

Figure 1. Node Clustering in vehicular ad-hoc networks (VANETs).

MOBIC [11] is one of the commonly adopted classical approaches proposed, and it works effectively in MANET for the CH election, but in VANETs, node mobility is higher than MANETs. Therefore, a similar solution cannot be utilized for VANETs. Currently, many conventional approaches are proposed for VANETs like message dissemination in vehicular networks on the basis of agent technology (NCABAT) [12]. This technique classifies nodes into three different categories as context agent, optimization agent, and cluster head for clustering network. For simulation, NCABAT is tested with only 60 nodes having a fixed 160 m transmission range in 1300 m x 700 m grid size. It is compared with the multicast operation of the ad-hoc on-demand distance vector routing protocol (MAODV) [13]. NCABAT outperforms MAODV, but it does not provide an ideal clustering solution for the simulated network.

In previous studies, like an efficient clustering algorithm in vehicular ad-hoc networks (VWCA) [14] proposed by Daeinabi for VANET's, VWCA is an extended version of weighted clustering algorithm (WCA) [15], proposed by M. Chatterjee for MANET's. WCA assigns static weights to various network parameters, like transmission range and node ID, for all nodes to select CH. VWCA also uses static weights, providing a single outcome for different network settings. Similarly, in passive clustering aided routing protocol for vehicular ad-hoc networks (PassCAR) [16] proposed by Wang, this method utilizes a passive clustering mechanism, a technique where information of control channel is not utilized.

The process of clustering is based on the information collected from data packets. The performance of PassCAR is evaluated by a maximum node density of 350 nodes. PassCAR performs identically in many cases as compared to the original passive clustering mechanism but has failed to optimize network performance. Similarly, all conventional mechanisms suffer from optimization problems for various communication scenarios. These problems are known as NP-hard/non-convex [17] problems; for such type of problems, evolutionary algorithms are more suitable due to the ability to solve the problems by using the nature-inspired mechanisms [18]. For example, the natural behavior of birds and insects or the function of genes in living things. This makes evolutionary techniques more adaptable to any optimization problem. No free lunch (NFL) [19] theorem is another motivational factor behind the use of different algorithms for optimization problems in various domains. NFL states that any optimization technique cannot perform optimally for all optimization problems. The architecture of drone assisted VANET is elaborated in Figure 2.
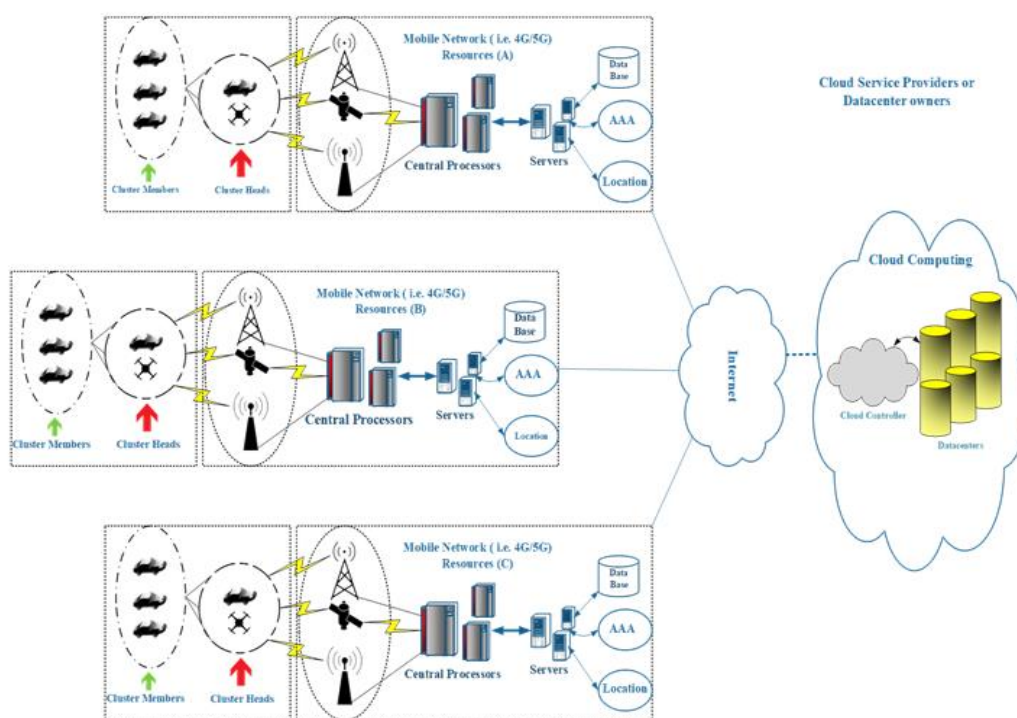

Figure 2. Flying wireless backbone assisted architecture.

This study proposed an algorithm for vehicular node clustering. This algorithm optimized the process of clustering based on several parameters (nodes direction, network area, communication link capacity, node density, and transmission, range, etc.). This algorithm was based on a grasshopper optimization algorithm (GOA) [20]. To the best of our knowledge, this mechanism is being utilized for the first time in VANET's. The swarming behavior of grasshoppers is mathematically modeled, mainly considering social attraction and repulsion among individuals to obtain output in the form of a total number of clusters in each scenario.

2. Literature Review

Vehicles sharing similar properties are grouped together, forming a cluster. It is done normally in two different modes, namely, distributed mode and centralized mode [21]. In the first mode, there is the absence of a governing node in a cluster. So, each node is responsible for its own network management and communication functions. For more reliability, in the second mode of clustering architecture, a vehicle is chosen as a CH for centralized communication and network management-related tasks. There are various clustering strategies and mechanisms in the literature to solve problems in VANETs

domain [22]. Most of them follow methods purely proposed for MANETs for cluster formation. However, due to major differences, these methodologies cannot perform optimally for any VANETs scenario. Traditional methods like VWCA [4] is an extended version of WCA [5]; WCA is constructed for pure MANETs. VWCA uses a similar weighed cluster matrix approach, considering parameters like nodes direction, distrust values, and the entropy.

This technique has performed reasonably better in various scenarios but failed to provide optimal clustering solution, and VWCA has only produced a single solution for each scenario. For this reason, that mechanism stays dependent on static weights, using this similar kind of solution, and is computed for the various different types of network states. This behavior is not ideal for real-world VANET applications [1,2]. A hybrid bio-inspired bee swarms routing protocol for safety applications in VANETs (HyBR) [23]. This bio-inspired approach is based on the swarming behavior of artificial bees for VANETs unicast routing. To improve the reliability of safety applications, this technique combines a bio-inspired algorithm with conventional geographical routing for improved performance. It is called HyBee; it has provided a better solution for different scenarios as compared to existing techniques, such as ad-hoc on-demand distance vector (AODV), greedy perimeter stateless routing, and greedy perimeter stateless routing (GPSR) protocols. However, it has failed to provide optimal clustering solutions and used only 1000 m × 1000 m grid size for experimentation.

In [24], binary artificial bee colony (BABC)-based technique spanning tree structure is purely utilized, and the least/minimum spanning tree (MST) is beneficent for better communication. The function of the spanning tree is to communicate nodes without loops. For simulation maximum, 16 nodes are simulated with only a single hit prediction parameter. BABC is evaluated against the Kruskal algorithm; BABC has performed better because of its dynamic tendencies and evolutionary capacities. In experimentation for performance analysis, the only vehicle to roadside (V2R) mode is used. Another swarm-based technique [25] is projected to VANETs for optimal routing solutions. It uses the ant colony optimization (ACO) approach and has been compared with comprehensive learning particle swarm optimization (CLPSO) and multi-objective particle swarm optimization (MOPSO) [26]. It has performed optimal than two existing techniques, providing a minimum number of CH's for various network scenarios. But still, there is a gap in providing a minimum number of clusters to provide more enhanced VANET services. Similarly, recently proposed protocols like [27] and [28] are based on SI techniques, namely, dragonfly and grey wolf optimization algorithms. Individually, these protocols have performed better as compared to present techniques CLPSO, MOPSO [29], and ACO [30]. Similarly, GWOCNET [31] and clustering algorithm for the internet of vehicles based on dragonfly optimizer (CAVDO) [32] have been proposed for clustering of vehicular nodes on the highways. The new clustering method for the internet of vehicles (IoV) is modeled as the hospital resident (HR) matching game. In particular, a stable matching between the cluster heads and ordinary nodes can be achieved with the proposed resident-oriented Gale–Shapley (RGS) algorithm [33]. Another approach [34] is based on coalitional game theory to VANET for the only vehicle to vehicle (V2V) communications. Furthermore, ad-hoc-based networking is performed to pursue full context awareness of vehicles. Nowadays, clustering has been introduced as one of the important factors in upcoming new wireless generations as well [35]. A clustering-based reliable low-latency routing scheme using the ACO method for vehicular networks [36] is used to enhance VANETs QoS. In this algorithm, ACO is used with two different schemes—AODV and clustering-based reliable low-latency multipath routing (CRLLR) scheme, where CRLLR is efficient in latency and number of beacons messages on the cost of more energy consumption and minimum reliability. In [37], ACO swarm-based technique and genetic algorithm (GA) [38], inspired by human genes, are combined to form a clustering protocol GA-ACO for VANETs. This protocol uses GA for feature selection, and then the outcome of GA is later utilized by ACO. It has performed better on a maximum of 4000 m × 4000 m and 1000 m × 1000 m grid size as compared to ACO, CLPSO, and MOPSO. However, intermediate network areas are not considered in the simulation to provide optimal solutions for mid-range network coverage areas. Secondly, in

this approach, static control weights are used, like previously utilized techniques. Dynamic control weights can cause more diverse outcomes for different communication settings.

An intelligent naive Bayesian probabilistic estimation practice for traffic flow to form stable clustering in VANET (ANTSC) [39] is proposed for stable clustering in VANETs. This technique is based on a conventional artificial intelligence approach. ANTSC has performed better in various network scenarios to form stabilized clusters as compared to existing algorithms—traffic flow-based clustering (TFB) [40] and traffic management in VANET using clustering [41]. However, the ANTSC technique has failed to provide an optimized clustering solution for communication scenarios. To increase more stability, the infrastructure-based approach is used as software-defined network-enabled 5G-VANET [42]. In this technique, dual CH's are s/elected for network function improvement. 5G-VANET has performed better in different network settings as compared to no clustering and centralized clustering schemes but does not construct the best possible solution for 5G [43]-enabled network. GOA is one of the most recently proposed swarm-based algorithms, possessing two different swarming behavior in two different life cycle stages of grasshoppers. In the first larval stage, grasshoppers tend to move slowly, while in adulthood period, large scale and fast movements are major features for food searching and social interaction among grasshoppers.

To our best knowledge, this technique is being used for the first time as a clustering protocol in the VANET environment. To optimize the number of clusters, its unique and dynamic swarming behavior motivated us to develop an algorithm for VANETs called 'GOA'. Secondly, we proposed a case study for extended Unmanned Aerial Vehicles-based flying backbone environment to elaborate its application in FANET and 5G infrastructure-based scenarios.

3. Intelligent Clustering via GOA

Unpredictable traffic density and dynamic network settings require a more efficient clustering technique to increase overall network stability; it can be increased by reducing the number of clusters. Minimum clusters mean few CH's for increased communication efficiency in highly dense environments because CH's are responsible for the exchange of information among all CM nodes. Therefore, for efficient CH's election, the swarm-based technique has allowed GOA to provide a solution set of efficient CH's for VANETs. In this framework, GOA simulates grasshopper swarming behavior for clustering, as shown in Figure 3. In GOA, each search agent represents a solution set in the form of a complete route, containing vehicular node ID's elected as CH's.
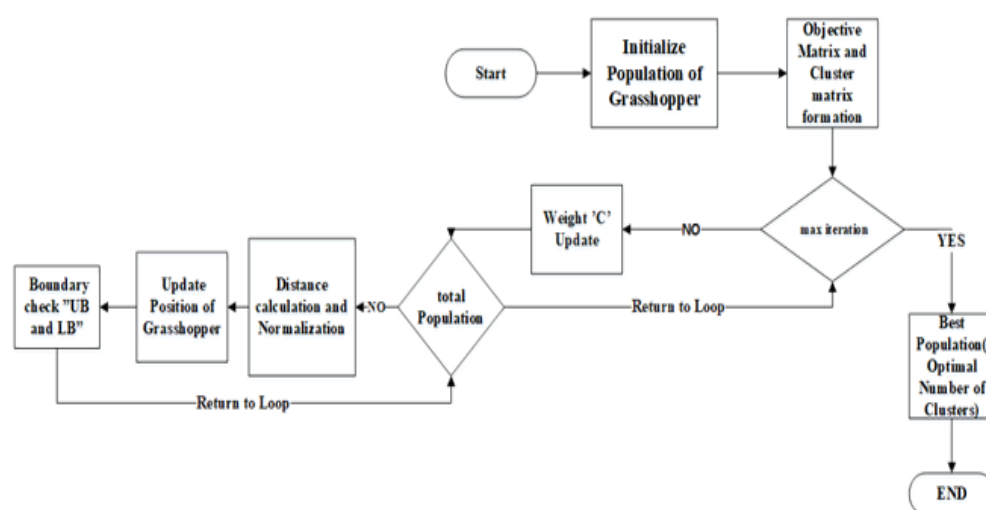

Figure 3. Flow chart of the proposed methodology.

Figure 3 represents the breakdown of different execution stages; the process is initialized with a random solution. Then, nodes are clustered considering one CH per cluster, and its CM nodes are

assigned from a given set of vehicles to form a clustered matrix. After this, a weighted function is used to construct the objective matrix, containing two variables w1 and w2 (i.e., weights assigned to objective functions). In the next stage, two-loop counters are used; in the first loop, weight c is updated according to a number of iterations to be used in the second loop for position update of the whole swarm. Hence, in this way, the optimization process continues for the whole population to reach its best position until a maximum number of iterations. At the end of this process, the main loop will return the efficient CH's elected so far.

There are few major requirements for a problem to be encoded and optimized by any optimization algorithm, stated as follows [44,45]:

- Multiple solution sets and subsets can be used to form a complete solution.
- Mechanism for the election of the best solution depends on the fitness of each solution set.
- It is desired but not compulsory for any technique to provide an optimal solution for all types of problems.

Algorithm 1 provides the pseudo code for GOA and contains a discussion of significant steps below.

Algorithm 1. GOA (grasshopper optimization algorithm) pseudo-code.
1.   Set all vehicles places on the highway (randomly)
2.   Set each node's direction (Randomly)
3.   Set the speed/velocity of each vehicle
4.   Make Mesh topology
5.   Compute the inter-vehicle distance with the corresponding nodes in the above topology
6.   Initialize Grasshoppers in Search space
7.   Initialize C_{min} and C_{max}
8.   Calculate fitness of initial swarm
9.   FOR iterations = 1 to stall iteration (stall iteration is set to 10)
10.   WHILE (Nodes! = empty)
11.   Nodes clustering = All Node
12.   End while
13.   While 1 <= iterations (While iterations are greater or equal to one)
14.   Update C using $Gf_k = G * \overset{\frown}{E}_g$
15.   For 1 to Population size (Dragonflies)
16.   Normalize distances Between Search agents
17.   Position Update of current Search Agent
18.   Bring all Agents with in Upper Bound (UB) and LB
19.   END FOR
20.   Update Best cost
21.   Iteration+1
22.   End while
23.   Best cost
24.   END FOR

3.1. GOA Pseudo Code

Line# 1–8 of the pseudo-code present in the above table are the initialization steps. The random position is used to start a vehicle in 2d (two-dimension) direction with random speed. The parameters mentioned in line# 1, 2, and 3 (each node's location on the grid, direction, and speed/velocity) can be considered as input parameters for real-time applications. After this random search, space creation for line # 9–14 of the pseudo-code fitness of grasshoppers is calculated to form a cluster. In each

iteration, weight c and position of each vehicle are updated to get and measure new fitness values from search space for optimal results. The output of this algorithm will be the near-optimal clusters with a balanced load. Load balancing means that the clusters are formed in a way so that every cluster head has balanced cluster members.

3.2. Fitness Function used in GOA

For the fitness calculation of each grasshopper, Equation (1) is used as a multi-objective fitness function.

$$Fitness_k = \omega1 * function_1 + \omega2 * function_2 \tag{1}$$

where $\omega1 = \omega2 = 0.5$ as equal weights for both fitness functions. In GOA, $function_1$ is Δ difference for clusters in route length α. While $function_2$ is taken as the sum of CMs's distance from CH's for all clusters.

$$f_{unction\ 1}(\Delta\_D) = \sum_{x=1}^{|\alpha|} Absolute\left(degree^{\circ} - |CMs_x|\right) \tag{2}$$

where Absolute is a function to get absolute value, and $|CMs_x|$ are CMs of current cluster x from complete route length $|\alpha|$ degree $^{\circ}$ is the constant value representing the degree of the density for each cluster. It can be specified by the user as a lower value for lower density and higher for the denser cluster. For example, when Δ_D approaches zero, clustering will be optimum. The smaller difference for the value specified by the user results in more optimal clustering in terms of user specification. $Function_2$ fitness function can be calculated with Equation (3) mentioned below:

$$\begin{aligned} &f_{unction\ 2}(sum\ of\ Distance) \\ &= \sum_{x=1}^{|\alpha|}\left(\sum_{Q}^{cHD(q)} Eucledian\ Distance\left(cHD_{(q)}, cMR_{Q,q}\right)\right) \end{aligned} \tag{3}$$

where first Euclidian distance is calculated for all $|\alpha|$ clusters. It is a sum of the inter-vehicular node (IVN) $CMs_{Q,q}$ distance from $cHD_{(q)}$) for each cluster (q) in total clusters$|\alpha|$.

3.3. Equational Operators

$$\varphi k = Sf_k + Gf_k + Ad_k \tag{4}$$

where φk defines the position of the k-th agent, Sf_k is the variable for social attraction and repulsion forces, Gf_k is the force of gravity for the k-th search agent, and Ad_k is the air drift variable. It can be used with random behavior, then the equation can be written as $\varphi k = rand_1*Sf_k + rand_2*Gf_k + rand_3 *Ad_k$, where $rand_1$, $rand_2$, and $rand_3$ are random numbers in the interval [0, 1].

$$Sf_k = \sum_{\substack{l=1 \\ l \neq k}}^{n} s(d_{lj})\hat{D} \tag{5}$$

where d_{ij} denotes the distance, the function used to calculate in between l-th and j-th agent. It is multiplied with s' (social force factor) to identify its strength, as shown below in Figure 4A. Social force is calculated as follows:

$$s(\gamma) = fi * e^{-l} - e^{-\gamma} \tag{6}$$

where l is length scale, providing attractiveness scale, and f_i is attraction intensity. Following equation shows how to calculate Gf function of gravitational force:

$$Gf_k = -G * \hat{E}_g \tag{7}$$

where $\hat{E}_g$ is a vector (unity) to the center of the earth, and G is gravitational constant. The Ad_k factor is calculated as below (Equation (8)):

$$Ad_k = Dc * \hat{E}_{wind} \tag{8}$$

where Dc is drift constant, multiplied with $\hat{E}_{wind}$, vector (unity) to show the direction of the wind. Before the adult stage of agents, they have no wings; hence, they move with the wind direction. Replacing the values of Sf_k, Gf_k, and Ad_k, the equation will become like the following equation:

$$\varphi k = \sum_{\substack{l=1 \\ l \neq k}}^{n} s(|\varphi_l - \varphi_k|)(\varphi_l - \varphi_k)/d_{ij} - G * \hat{E}_g + Dc * \hat{E}_{wind} \tag{9}$$

where values of Sf_k, Gf_k, and Ad_k are calculated for (n) number of agents.

$$\varphi_k^D = c\langle \sum_{\substack{l=1 \\ l \neq k}}^{n} c * (UB_D - LB_D)/2 * s(|\varphi_l^D - \varphi_k^D|)\varphi_l - \varphi_k/d_{ij}\rangle + \hat{B}_D \tag{10}$$

where φ_k^D shows the position of k agents in dimension D. First, c is like inertia weight of particle swarm optimization, and second, c is control function for attraction zone. It decreases linearly, and UB_D and LB_D are boundaries as upper and lower bound of search space. $\hat{B}_D$ indicates the best agent found so far in the search space. Actually, these variables (e.g., the vector to the center of the earth, and the vector to show the direction of the wind) are used in the grasshopper algorithm to maintain the balance during the flight.
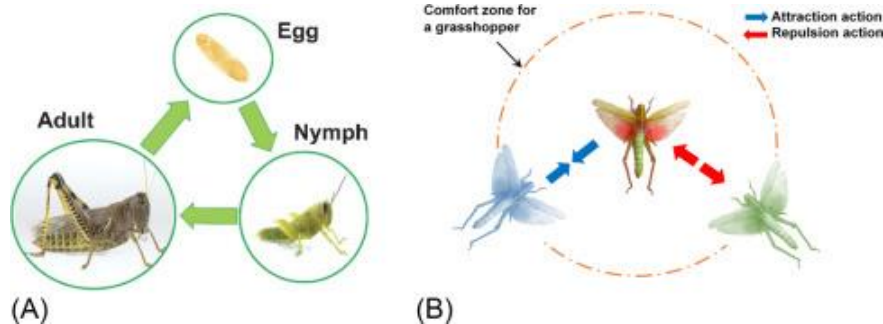

Figure 4. (**A**) Major stages in the lifecycle of grasshoppers, (**B**) Social interaction and swarming behavior of grasshoppers.

4. Results and Discussion

The results obtained from the preliminary analysis of all techniques with network size equal to 1000 m × 1000 m are shown in Figure 5. It is apparent from this figure that more transmission range and smaller network size results in few numbers of clusters. However, GOA and clustering algorithm for the internet of vehicles based on dragonfly optimizer (CAVDO) are forming a minimum number of clusters with 600 m transmission range and 30 network nodes as compared to grey wolf optimization-based clustering algorithm for vehicular ad-hoc networks (GWONET) and ACO-based clustering algorithm for VANET (CACONET). While for the minimum transmission range, CACONET is performing better than all other protocols. No significant results can be found with intermediate transmission range values because all techniques are performing nearly equivalent except CACONET. Simulation parameters used for experimentation are listed in Table 1.
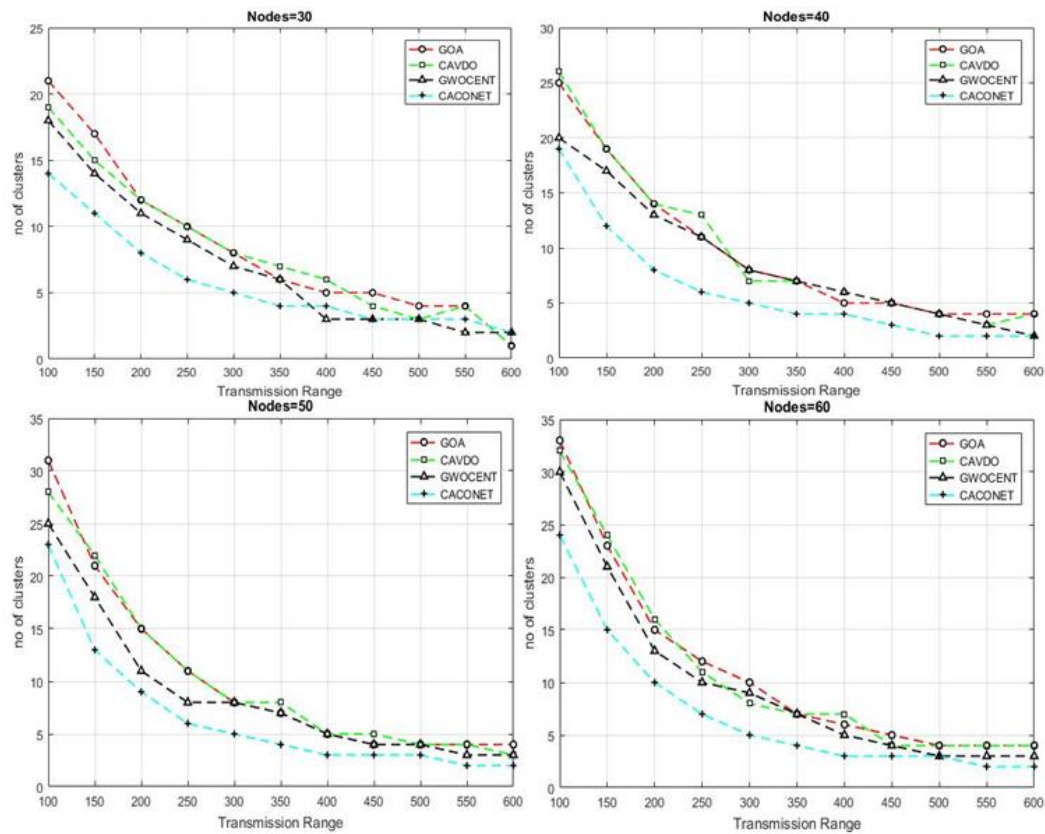
Figure 5. The number of clusters vs. Tx range for $1 \text{ Km}^2 \times 1 \text{ Km}^2$.

Table 1. Simulation parameters.

Parameters	Values for GOA
Population size (Dragonflies)	100
Maximum iterations	150
c=cMax-l*((cMax-cMin)/Max_iter)	0–1
Vehicle velocity range	22 m/s–30 m/s
Simulation area	$1 \times 1 \text{ km}^2$, $2 \times 2 \text{ km}^2$, $3 \times 3 \text{ km}^2$, $4 \times 4 \text{ km}^2$
Maximum acceleration	1.5 m/s2
Minimum distance B/W vehicles	2 m
Maximum distance B/W vehicles	5 m
Lane width	50 m
Total lanes	8
Transmission range	Dynamic
Mobility model	Freeway mobility model
Simulation runs	10
W_1 (weight of first objective function)	0.5
W_2 (weight of second objective function)	0.5
Simulation tool	Matlab 2018a
CPU	intel i7-5500u
CPU frequency	2.4 GHz
RAM	8 GB
Operating system	Windows 10 (64 bit)

4.1. The Number Of Clusters Vs. Transmission Range For Grid Size 1 KM² × 1 KM²

From Figure 5, we can see that there is a positive correlation between the transmission range and the number of clusters. When the transmission range is increased, a smaller number of clusters are formed and vice versa, also in case of node density and grid size. It can be observed for this

network scenario, having a node range of 30 to 60 vehicles in a segment of 1000 m × 1000 m. All the techniques are performing equally when the transmission range is reaching to its maximum limits. It can also be seen that there is no significant difference between GWOCNET, CAVDO, and GOA, but CACONET is performing better than all other techniques for the minimum simulation area. The most striking result from data is that when even CACONET is performing better than the other three techniques, it is negatively influenced by the increase in network size that is opposite in GOA, CAVDO, and GWOCNET.

4.2. The Number of Clusters Vs. Transmission Range for Grid Size 2 KM^2 × 2 KM^2

Figures compare the inter-correlation among the four measures of clustering protocols. These parameters are the number of network nodes, transmission range, network area, and the number of clusters formed by each protocol. The interesting fact which can be observed by this data is that the higher the node density the higher the number of clusters and vice versa. GOA is performing better than CAVDO when the transmission range is 100 m with 30 vehicles. When we compare it with GWO, the results are significant when the transmission range is increased from 300 m, and GOA is providing minimum cluster. In Figure 6, the number of clusters is presented on the y-axis, while the x-axis shows the transmission range for vehicular nodes. It can be seen that the transmission range and the number of clusters are inversely proportional. When we increase the transmission range, the number of clusters is decreasing. In this scenario, GOA is performing better than GWOCNET and CAVDO in many cases. While for 60 network nodes, CACONET is providing a minimum number of clusters as compared to all other protocols.
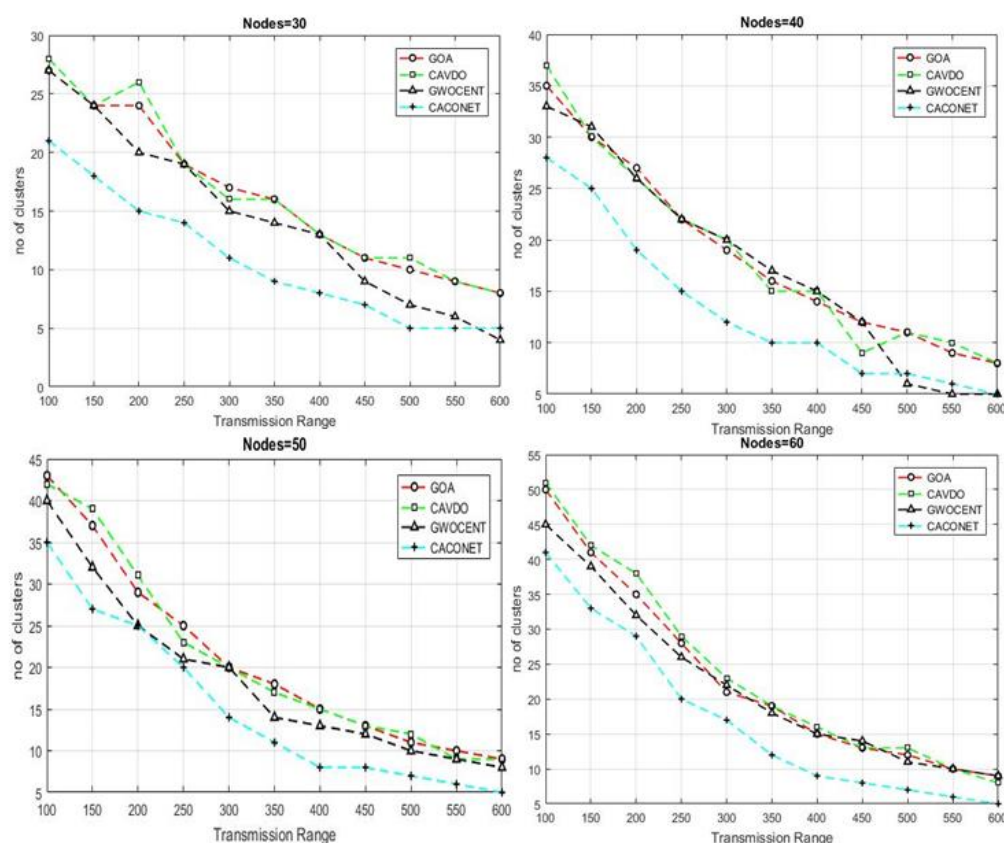

Figure 6. The number of clusters vs. Tx Range for 2 Km^2 × 2 Km^2.

4.3. The Number of Clusters Vs. Transmission Range for Grid Size 3 KM^2 × 3 KM^2

Figure 7 illustrates the numerical values for the grid size of 3000 m × 3000 m. What is interesting in this data is that minimum and a maximum number of clusters are increased for all protocols with

respect to 1000 m × 1000 m and 2000 m × 2000 m grid size. This is the strong evidence for the negative effect of inter-vehicle distance to the number of clusters. As can be seen from the data in Figure 7, the performance of CACONET is degrading with node density, and the simulation area is increased. GOA, CAVDO, and GWOCENT are more stable in function with respect to CACONET.
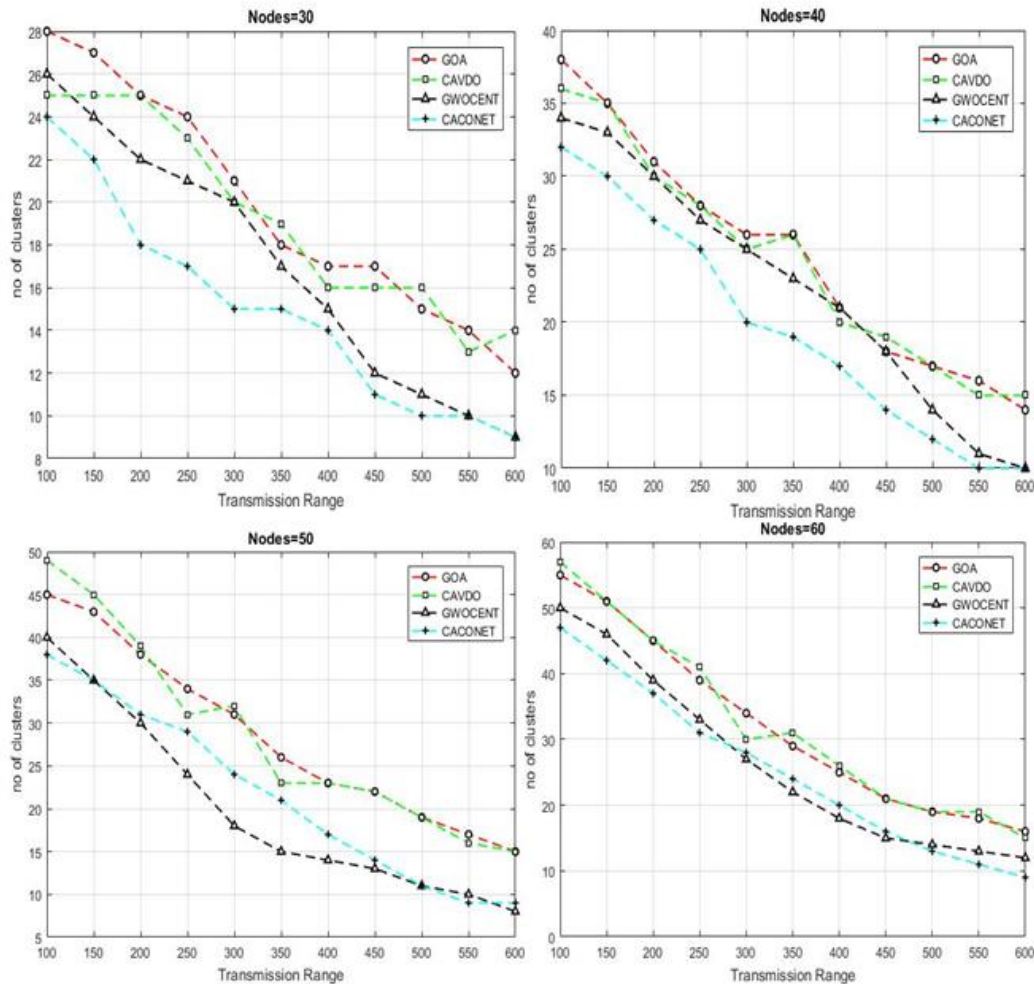

Figure 7. The number of clusters vs. Tx Range for 3 Km^2 × 3 Km^2.

4.4. The Number of Clusters Vs. Transmission Range for Grid Size 4 KM^2 × 4 KM^2

In Figure 8, the number of clusters is presented for GOA, CAVDO, GWOCNET, and CACONET protocols. It contains the number of clusters for transmission range of 100 to 600 m, with a range of node density varying from 30 to 60 nodes and 4000 m × 4000 m area. The correlation is clearly visible in Figure 8 that increased grid size, and traffic density is causing a greater number of clusters only in the case of CACONET. While proposed GOA protocol is performing ideal by providing an optimal number of clusters in all experimented scenarios. In Figure 8, there is a trend of a decrease in the number of clusters when the transmission range is being increased. In all the scenarios, GOA has performed optimally by providing a minimal number of clusters for the whole network. Significantly, when the transmission range is equal to 100 m, node density is 30, and the simulation area is 4000 × 4000 m. The overall trend shows that ACO has performed worst in all cases with respect to the proposed GOA technique.
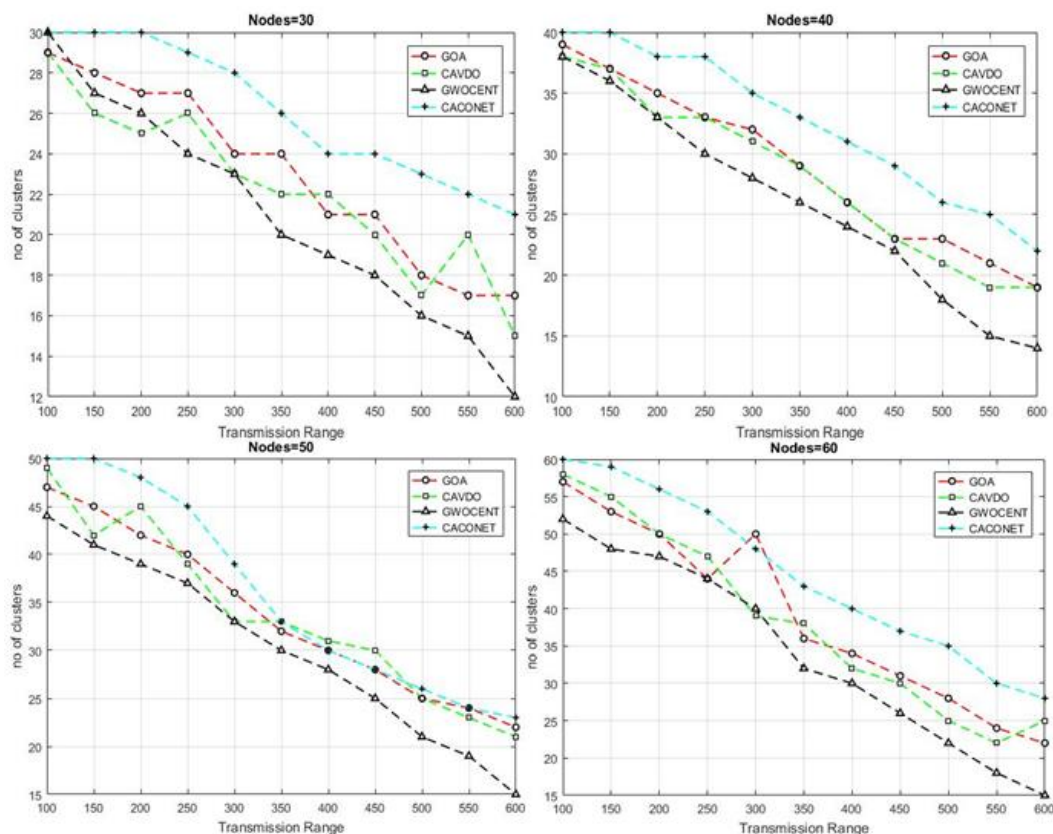
Figure 8. The number of clusters vs. Tx Range for 4 Km^2 × 4 Km^2.

5. Conclusions and Future Directions

In VANETs under different node density and traffic conditions, the effective exchange of information is very challenging. This paper proposed a GOA swarm-based clustering protocol for better communication by electing efficient CH's in low, medium, and high node density environment. GOA optimized network by providing a minimum number of clusters, and it is also visible in the results section that it performed better or near-optimal to CACONET, GWOCNET, and CAVDO. Furthermore, CACONET was negatively influenced by increased node density, while the proposed GOA was minimizing the number of clusters for increased network density. These were the significant contributions of this study, providing various future directions. For instance, it can be used in the FANET domain with the additional feature of energy in its fitness function. Also, different swarming behavior can be used as well, e.g., salp swarm algorithm.

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