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Grey wolf optimization based clustering algorithm for vehicular ad-hoc networks☆

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ABSTRACT

In vehicular ad-hoc network (VANETs), frequent topology changes occur due to fast moving nature of mobile nodes. This random topology creates instability that leads to scalability issues. To overcome this problem, clustering can be performed. Existing approaches for clustering in VANETs generate large number of cluster-heads which utilize the scarce wireless resources resulting in degraded performance. In this article, grey wolf optimization based clustering algorithm for VANETs is proposed, that replicates the social behaviour and hunting mechanism of grey wolfs for creating efficient clusters. The linearly decreasing factor of grey wolf nature enforces to converge earlier, which provides the optimized number of clusters. The proposed method is compared with well- known meta-heuristics from literature and results show that it provides optimal outcomes that lead to a robust routing protocol for clustering of VANETs, which is appropriate for highways and can accomplish quality communication, confirming reliable delivery of information to each vehicle.

1. Introduction

In current era, famous meta-heuristic techniques; Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO), are becoming popular in computer vision and machine learning community. In computer

Abbreviations: ACO, Ant Colony Optimization; ACROA, Artificial Chemical Reaction Optimization Algorithm; BBBC, Big-Bang Big-Crunch; BHA, Black Hole Algorithm; CACONET, Clustering algorithm based on Ant Colony Optimization (ACO) for VANET; CFO, Central Force Optimization; CHs, Cluster heads; CLPSO, Comprehensive Learning Particle Swarm Optimization; CN, Cluster nodes; CSO, Curved Space Optimization; CSS, Charged System Search; GA, Genetic Algorithm; GbSA, Galaxy-based Search Algorithm; GLSA, Gravitational Local Search; GWO, Grey Wolf Optimization; GWOCNETs, Grey Wolf Optimization Based Clustering In Vehicular Ad-Hoc Networks.; ITS, Intelligent Transportation Systems; MANET, Mobile ad hoc networks; MOPSO, Multi-Objective Particle Swarm Optimization; PSO, Particle swarm optimization; ROA, Ray Optimization Algorithm; SWOA, Small-World Optimization Algorithm; VANET, Vehicular ad hoc networks.

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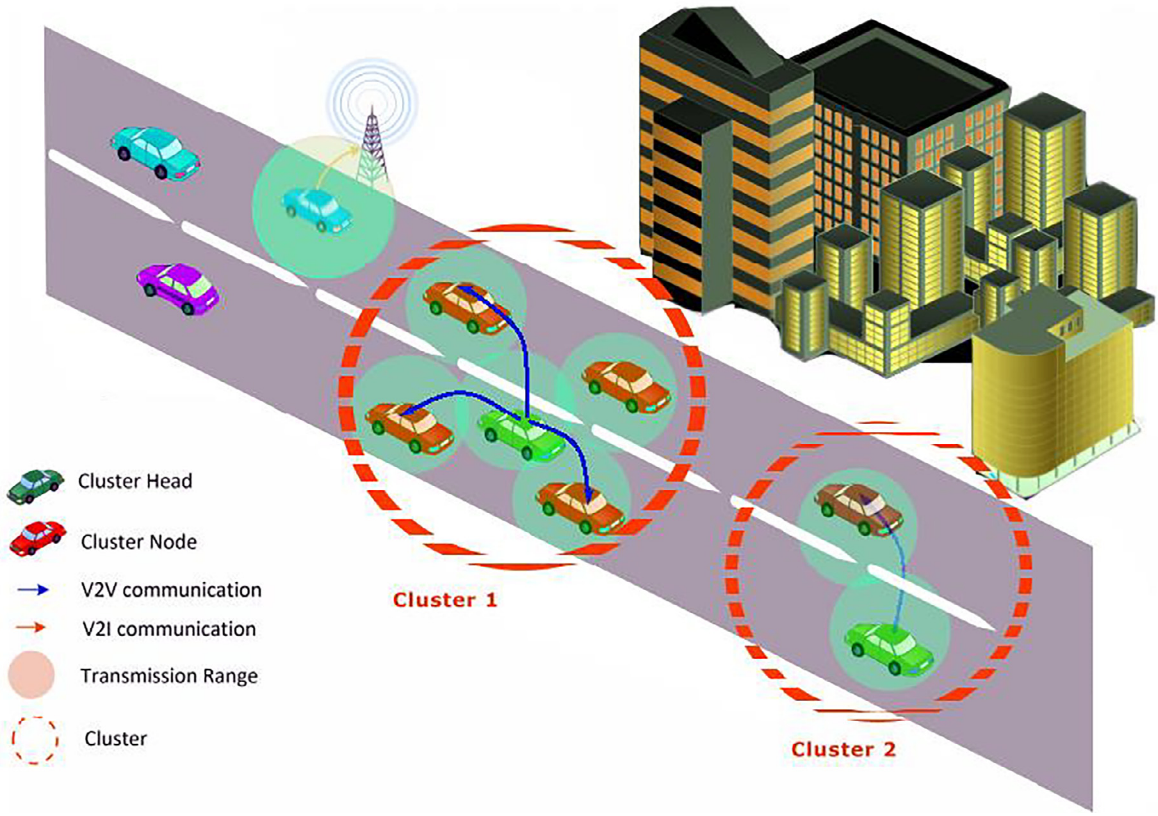

Fig. 1. Clustering in VANET's. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

science, meta-heuristics are playing a productive role and in many other fields as well. Due to the huge usage of meta-heuristics, it raises few questions. Why meta-heuristics techniques are now becoming more common as compared to any other methods. Scientists give the many logical answers regarding it. Flexibility, Deviation-free method, Simplicity/Easily Understandable, Local-optima avoidance are some of them. Flexibility of meta-heuristics algorithms increased the usage. These are enough flexible to solve the different problems of different natures. These methods, are lenient in applicability. Various meta-heuristics are derivation-free, because meta-heuristics solve the problems by using the randomness of variables. This method initiate with random solution, which exclude the calculation for the derivation of search space and make it more applicable for existing problems. Third, the meta-heuristics are imitative from the natural working or daily routine of animals, birds and insects etc., making it easy to understand and providing further chances for the researchers. Finally, these procedures focus on the explorations of working space, to reduce the stuck-ness of local solution. As, local solutions are not the proper solutions for any problem.

Vehicular ad-hoc network (VANET) is a primary branch of ad-hoc Networks in which transmission of data occurred between automobiles. In VANETs, there are also temporal or momentary creation of network for sharing of resources. VANETs is progressed to supplementary divisions based on method of communication. It contains Vehicle to Infrastructure (V2I), Vehicle to Vehicle (V2V), and hybrid communication (V2V-V2I). Vehicular network is dynamic network, in which nodes have inconsistent/random motion which causes frequently structural deviations of nodes. Consequently, this causes the network separation which results in the expiration of network. Its lifetime can be increased by forecasting the flow pattern or mobility pattern of vehicles, leading towards the extensive use of applications in commercially, multimedia, safety, emergency, managing of traffic applications. Moreover, Quality of Service (QoS) is mandatory for efficient transmission of data. Delay can be dangerous in scenarios such as safety and surveillance applications. Scalability is also one of the problems, which causes a lot of damage in the sustainability of network. Load balancing of the network must be managed for the lifetime of network. In this context, intelligent clustering algorithms, can play a vital role to create vehicular network more optimized, manageable, scalable and for equal distribution of network load. Clustering in network means, grouping of nodes on the basis of some likeness and unlikeness for achieving some specific goal with in the network. The likeness and unlikeness can be, by considering the different parameters such as distance among nodes, bandwidth availability etc. Clustering is also a proper method which varies from other clustering method on the basis of some rules and regulations. Cluster is formed by a collection of nodes. In the group (cluster), one of the cluster member or cluster node is selected as Cluster Head (CH). Fig. 1, shows the cluster spotted in red circle on a highway and their interaction with a blue colour. The size of cluster is

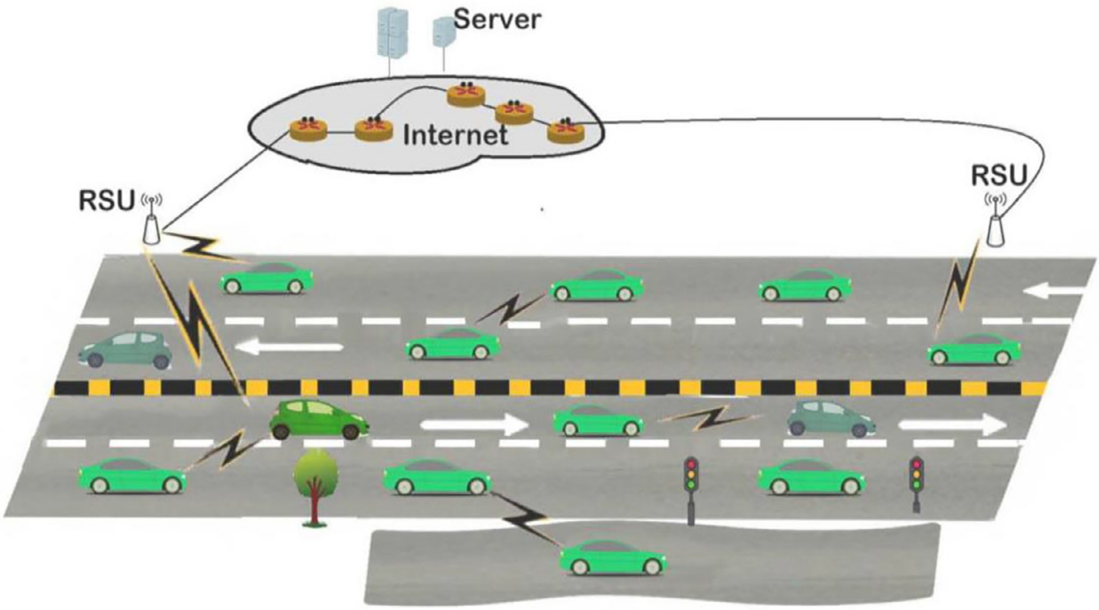

Fig. 2. Communication in vehicular ad-hoc networks.

proportional to the range of transmission. If the range of transmission is large, the size of cluster will be large, which means the number of members in the cluster will be more. Considering the number of clusters in the whole network is inversely to the range of transmission because the number of total clusters in the network will be less and optimal in mentioned problem. In the underlying issue, intelligent grouping of nodes in the VANETs for contact, the required traits are less or optimal number of cluster and CHs and long age of cluster. Longer the age of cluster, leads to good performance of network. Clustering also falls in one of the category of NP-hard problem. CHs play an important role in clusters. There are various responsibilities of CHs, i.e. the creation of cluster, ending of cluster, provision of resources to member nodes, and considering the topology of network for maintenance. CH is responsible to manage the communication between the clusters i.e. within the cluster members and outside the cluster with other available clusters in the network. MOBIC is the clustering algorithms which is working effectively in the Mobile Ad-hoc networks (MANETs), for the CH selection. The effectiveness of network is also measured by the stability of clusters. Cluster stability can also be understood in various ways regarding parameters; a) Ratio of changes of CH. b) Ratio of conversion of cluster nodes to CH. Fig. 2 given below help us to illustrate the communication between vehicles and different Road Side units (RSU).

The proposed framework grey wolf optimization based clustering algorithm for VANETs (GWOCNETs) is a novel approach and implemented for the first time in VANET environment, to the best of our knowledge. The objectives can be assigned as per user requirements in the proposed method. The social behaviour of grey wolf is pictured into four main levels (Alpha-α, Beta-β, Delta-δ and Omega-ω). The hunting tasks searching of prey, surrounding the prey, and attacking or confronting the target, performed by grey wolves are converted into mathematical model. This mathematical modelling makes it easy to understand the working of algorithm. Using all these concepts the appropriate numbers of cluster are extracted to optimize the mentioned problem. The final results are shown graphically so that better understanding can be built. Later on the comparison is done with the well-known existing meta-heuristics.

Swarm based cluster optimization can be used to find near optimal solution because clustering of network is NP-hard problem [1]. This is the basic motivation of proposed work, where clustering is performed using grey wolf optimization (GWO). In this scheme, the social intelligence of grey wolf in finding the best prey for the hunt. For which grey wolves update the position with respect to the movement of hunt. For the past decades, the algorithms' success has led to strongly practical-oriented interests. Although the theory of evolutionary algorithms is far behind the knowledge gained from experiments, there are theoretical investigations about some of their properties Evolutionary algorithms, which form a sub-class of meta-heuristic/bio-inspired algorithms, mimic some fundamental aspects of evolutionary process. They simultaneously search with a population of candidate solutions and associate an objective score as a fitness value for each one. The algorithms then select among the population to favour those solutions that are fit. VANET is one application of evolutionary algorithms among many others.

In a large scale network like VANET clustering is an elucidation for the scalability problem. Different clustering algorithms like multi-objective particle swarm optimization (MOPSO) [2], Comprehensive Learning Particle Swarm Optimization (CLPSO) [3] are implemented and compared with our proposed algorithm. Stability & connectivity of the network can be increased by different parameters (e.g., vehicle's direction, grid size, number of clusters in a network, the number of nodes/vehicles, and number of neighbours with respect to transmission range, speed of vehicles), also the overhead of the network can be

Table 1
Swarm Intelligence (SI) algorithms.

Algorithms	Description
Fruit Fly Optimization Algorithm (FOA) in 2012 [6]	Natural fruit fly foraging behaviour is capture in this algorithm.
Artificial Fish-Swarm Algorithm (AFSA) in 2014 [7]	Inspiration taken from the colonial behaviour of fish
Firefly Algorithm (FA) in 2010 [8]	Flashing behaviour of firefly to as a signal system to attract other fireflies.
Krill Herd (KH) in 2012 [9]	Nature inspired algorithm used to check the herding of krill for optimization.

Table 2
Physics-based algorithms.

Algorithm	Description
Black Hole (BH) algorithm in 2015 [10]	Bio-inspired algorithm taken from the concept of factual black hole.
Big-Bang Big-Crunch (BBBC) in 2014 [11]	The concept of theories for evolution of universe is taken to optimize the different NP-hard problems.
Curved Space Optimization (CSO) in 2012 [12]	In this approach Curved Space Optimization (CSO), the curvature of space stimulated by general relativity theory is used to expand the competence of a simple random search, and alter it to a very robust optimization tool.
Galaxy-based Search Algorithm (GbSA) in 2011 [13]	The modified hill-climbing algorithm is used to imitate the concept of galaxies.

Table 3
Evolutionary algorithms.

Algorithm	Description
Evolutionary Programing (EP) in 2012 [14]	Firstly developed to develop the finite state machine, Different evolutionary parameters are used in it (Genes, alleles, chromosomes etc.)
Evolution Strategy (ES) in 2013 [15]	Concept of adaptation and evolution is used in this algorithm.
Differential Evolution (DE) in 2006 [16]	The changes occurred due to crossover and mutation from one generation to another.
Genetic Programming (GP) in 2016 [17]	In this concept the problems are encoded as a set of genes and modified according to the problem needs.
Biogeography-Based Optimizer (BBO) in 2008 [18]	An evolutionary algorithm that is used to optimize the candidate solutions iteratively to reach up to measure of quality.

Table 4
Phases from exploration to exploitation of hunting.

Step I	Step II	Step III
Tracking	Pursuing	Attack
Chasing	Encircling	the
Approaching the prey	Harassing the prey	prey.

reduced. The proposed algorithm provides an effective approach to create vehicular clusters due to which overall performance of the network is enhanced.

The rest of the paper is organized as follows. Section 2 presents literature review about the meta-heuristics and its categories. Section 3 elaborates the proposed framework and new algorithm called as GWOCNETs. The graphically results as well as relevant discussion are presented in Section 4. Eventually, Section 5 concludes the work and outlines some advises for future works.

2. Literature review

There are two divisions of meta-heuristics: 1) population-based which works by imitating the random collection of solutions for the productive performance. This provides the focus on the explorations of working space, to reduce the stagnation of local solution. As, local solutions are not the proper solutions for any problem so it attracts towards the suitable solution. 2) Single solution provides a candidate which improves their characteristics with increment in the iterations. This means, the solution is improved after each iteration. .Meta-heuristics algorithms are typically divided into three main classes:

2.1. Swarm Intelligence (SI) algorithms

SI contains various widely familiar algorithms such as; Ant Colony Algorithm (ACO) proposed by Dorigo et al. [4]. The fundamental theme of ACO is extracted from the living or daily routine of ants. Ants spend their life in the nest and live in a colony. Ants live together and find the food in a pack. Ants always find the shortest and appropriate path for the food. A fluid called as pheromone is released by the ant during the travelling. By measuring the quantity of pheromone, other ants get the idea for the shortest path towards the target.

Table 5
Proposed GWOCNETs algorithm.

Pseudo code for proposed CGWONET Algorithm
1) Initialize all vehicles position randomly on the highway
2) Randomly initialize each vehicle direction
3) Initialize speed/velocity of each vehicle
4) Create a mesh topology among nodes, where each vertex represent a vehicle ID
5) Calculate the distance of each vehicle from the others, normalize and associate these distance values with the corresponding edges in the above mesh topology.
6) Initialize the grey wolf population X_i (i =1, 2, 3……, n)
For $i = 1$: n ## (n = search Agents)
End For
7) **For** q=1:10 # Number of iterations
8) Calculate **cluster_matrix**
9) Calculate objective_matrix
objective_matrix = w_1*delta_difference + w_2* distance_neighbor
#w_1 and w_2=weight
10) **While** (t < Max number of iterations)
11) **For** each search agent
12) Calculate the fitness of each search agent
a) X_α= the best search agent
b) X_β =the second best search agent
c) X_δ =the third best search agent
13) Calculate the value of linearly decreasing variable
[a=2-l*((2)/Max_iter)]
14) Update the position of the current search agents by using equations 5, 6, 7, 8, 9, 10 and 11.
15) **End For**
16) Update a, A and C
17) Calculate the fitness of all search agents
18) Update X_α, X_β and X_δ
19) $t=t+1$
20) **End While**
21) return X_α
22) Calculate the Best solution for the clusters
23) **End For**
Total number of Cluster = Best solution number of clusters

Kennedy [5] proposed the Particle Swarm Intelligence (PSO) in which behaviour of birds are implemented for solving the different problems. As birds live in a swarm and search the food in a pack. These birds also maintain their local best, personal best and global best for searching the appropriate target. Some SI techniques proposed are mentioned in Table 1.

2.2. Physics-based algorithms

In physic-based, the physical principles of nature are followed to optimize the research problems. The variation of this method from other is that it follows the physical rules (Rules of nature). Search agents are deployed randomly, and they move in search space by following the physical behaviours of natural phenomena. Some of the physics-based optimization algorithms are laid down in Table 2.

2.3. Evolutionary algorithms

In this method, the theme of evolution of nature, is used to solve the problems. Genetic Algorithm is one of the well-known bio-inspired algorithm in which process of mutation and crossover is used. Some of the evolutionary algorithms are as described in the Table 3.

Table 6
Simulation parameters for GWOCNETs.

Parameters	Values
Population size (Particles)	100
Maximum iterations	150
Inertia weight W	0.694
Lower bound (lb)	0
Upper bound (ub)	100
Dimensions	2
Lane width	50m
Total lanes	8
Transmission range	10 m–60 m
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
Nodes	30, 40, 50, 60
A (Linearly decreasing factor)	[0–2]

Learning Factor[1]

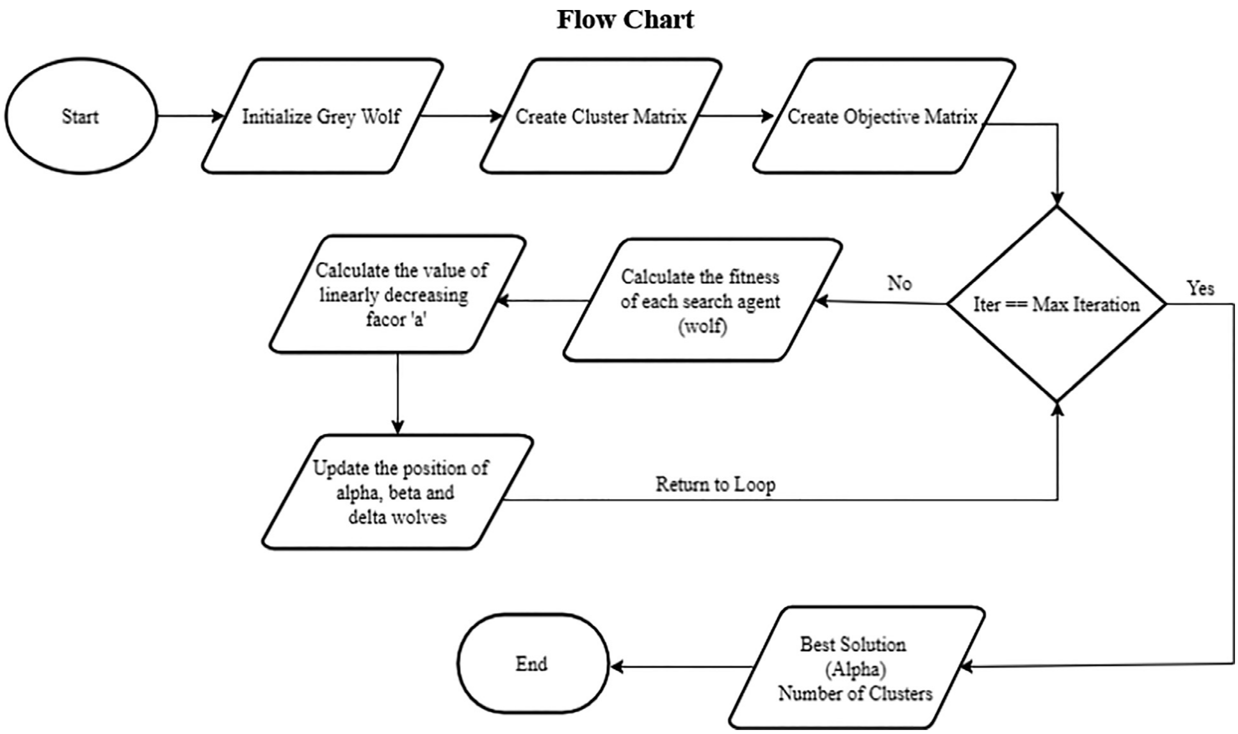

Fig. 3. Flow chart of GWOCNET.

These algorithms solve the optimization problems. A weighted clustering algorithm is proposed by Chatterjee et al. [19] in this algorithm the election of CH is dependent on the weight of node while the weight of nodes is dependent on diverse parameters like battery power, mobility and transmission range. Particle Swarm Optimization (PSO) based algorithm is proposed by Shahzad et al. [3] Comparative Learning Particular Swarm Optimization (CLPSO) is a variant of PSO, the proposed algorithm is for MANETs. This algorithm provide a solution set with adequate numbers of clusters, different parameters like ideal degree, mobility, transmission power and energy of the nodes are considered by this approach. In this approach each parameter has some weight similarly as in WCA. The CH is elected on the basis of these weights, and this CH is responsible for communication with cluster nodes as well as with the adjacent CHs. Another variant of PSO is proposed by Hamid at al. [2] named as MOPSO for MANETs. This algorithm provides more than one solutions according to the user selected parameters, while the predecessor versions of this algorithm provides single solution which is not sufficient for continues problems like clustering. COCANET [20] is also one of the methods used for the clustering in VANETs. The concept of this technique is taken from the ant's colony optimization. The load balance factor and complexity is also measured in VANETs by using ACONET [21]. There is a gap of improvement for optimizing the number of clusters which should be addressed so that clus-

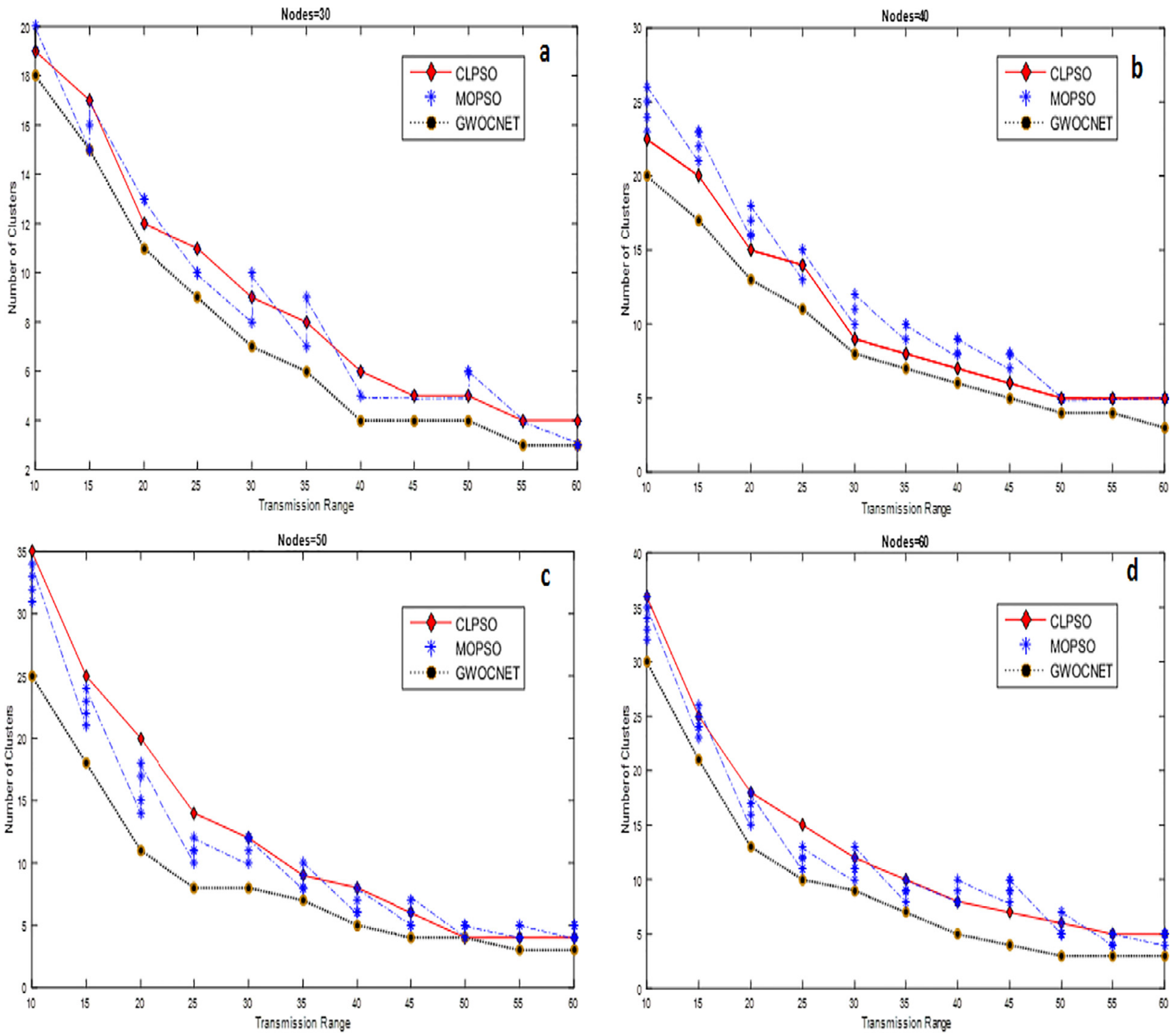

Fig. 4. Number of clusters vs. transmission range in case of CLPSO, MOPSO and GWOCNETs in 100 m × 100 m grid size by fixing nodes from 30 to 60.

tering in VANETs will deliver more optimized solution. Oranj et al. [22] the authors argued that although these protocols are directly affected by change in environmental parameters but these parameters are usually ignored even though it affect the throughput and performance. Different methods of clustering are also used. Baker and Ephremides [23] proposed the idea based on the identity of each node. According to them, a unique ID will be assigned to each node. A node which will have the lowest ID, will be selected as CH. Gerla and Tsai [24] proposed the technique for the selection of CH by using topology based clustering. In this method number of neighbours is calculated with each node which is called as degree of node. The node having the larger degree will be selected as CH. To the best of our knowledge, there is no such method implemented for solving the clustering problem in VANETs by using the grey wolf optimizer.

3. Proposed framework

This section discussed the proposed algorithm, which is extracted from the social behaviour of grey wolves. Initially the data is randomly generated according to the parameters (Number of nodes, Transmission range and grid size). Afterward, the network is built by the deployment of nodes in the grid. The clustering is made on the basis of their likeness or same features of nodes. These features are node's speed, direction, location, position and many more. For creating the efficient clustering, it is necessary that a node should be in one cluster only. Simultaneously, nodes should not be able to be a member of more than one cluster. In each cluster there is a CH who is responsible for managing the whole cluster and its member. CH also looks towards the new nodes and out-going nodes from the clusters. CH also manages the occurrence of

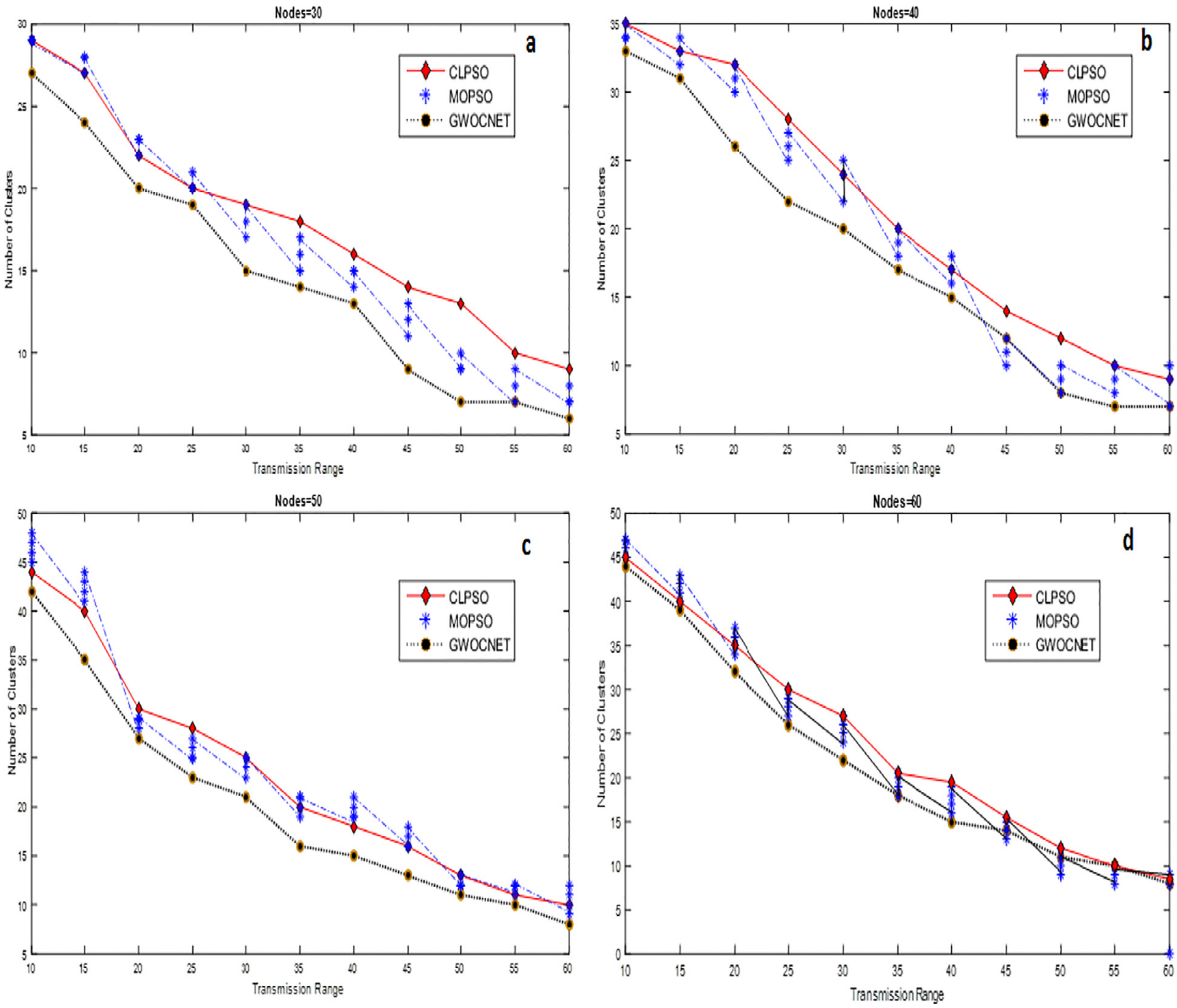

Fig. 5. Number of clusters vs. transmission range in case of CLPSO, MOPSO and GWOCNETs in 200 m × 200 m grid size by fixing nodes from 30 to 60.

node not more than a cluster. Now come to the main research question that how Grey Wolf works for creating the optimized number of clusters. Grey wolf is a member of Canidae family. They are normally in a group of 5–12 members.

The pyramid of grey wolf initiate from alpha (α). α (alpha) gender can be male or female. Alpha is a known as leader in the pack. They gave the instruction to others. Other wolves keep it tail down to show the respect of the alpha for obeying the instructions. The main decisions of whole pack are usually taken by the alpha wolves. These decisions contains sleeping, wakeup time and many mores. Alpha wolves got the natural skills for organizing the pack. Alpha also keeps the pack well disciplined. After the alpha wolf, there is position of beta (β) grey wolves. These can also be male and female, betas are considered as second in the hierarchy of grey wolves. These wolves support the alphas for making the decision and betas help the alphas for implementation of their instruction to the lower level of grey wolves in the packs. Betas wolves are used by the alphas for the feedback purpose as well. If any of the alpha wolves died then one of the betas wolf is promoted to alpha wolf. Third order of grey wolves is Delta (δ). These wolves are categorized into spies, guards, predators and caretakers. Delta wolves help to protect the complete pack, also they keep eyes on the boundaries so that in case of danger counter measures can be taken for the pack. Hunters (Delta) provide the food for the others, caretakers look after the aged, weak and sick wolves in the pack. If case of death of beta wolf the senior delta wolf is promoted to beta wolf.

Table 4, depicts the four main steps taken by the grey wolf from exploration (searching) to exploitation (attacking). Omega exist in the last position of grey wolves. Due to the last in the position of wolves they always have to pay more than others in return of very small reward. Omega wolves also seem as babysitters, with no importance individually in the pack but lost of omega wolves also creates the problem. They are allowed to eat lastly after hunting. Death of delta promotes the any one of the omega to delta. There are some important phases of the grey wolf for the hunting as explained below.

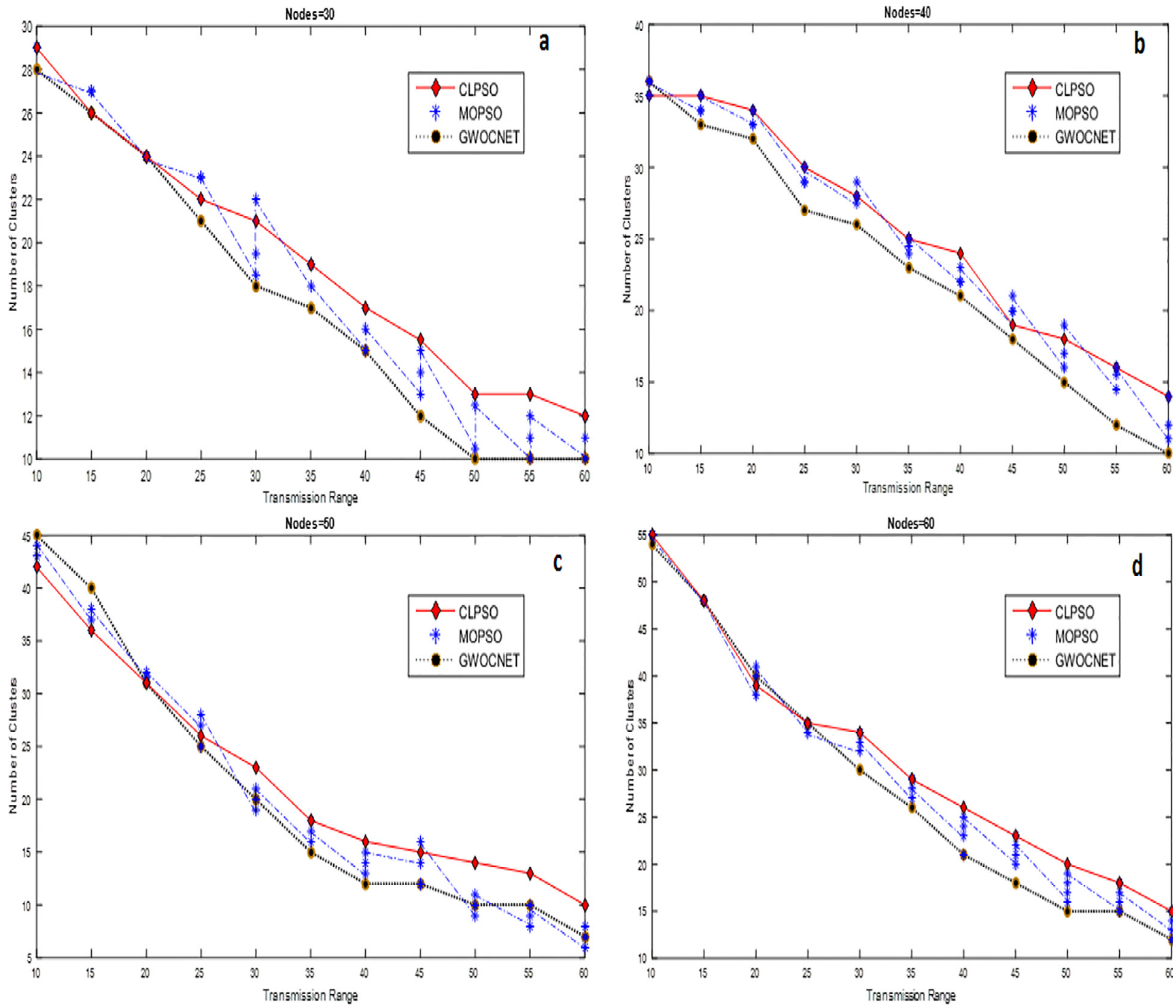

Fig. 6. Number of clusters vs. transmission range in case of CLPSO, MOPSO and GWOCNETs in 300 m × 300 km grid size by fixing nodes from 30 to 60.

3.1. Social hierarchy

Alpha (α) is considered as the fittest solution in the ordering of grey wolf optimization. Beta (β) is considered as the second most and consequently delta (δ) and omega (ω). α, β, δ is used for the guidance for the hunting purpose. Omega (ω) wolves just follow all three of upper hierarchy.

3.2. Encircling prey

Grey wolf encircle the prey during the process of hunting as;

$$\vec{D} = \left|\vec{C}.\ \vec{X_P}(t) - \vec{X}(t)\right| \tag{1}$$

$$\vec{X}\ (t+1) = \vec{X_P}(t) - \vec{A}.\vec{D} \tag{2}$$

where A and C are co-efficient vectors, X_p is the position vector of prey, X is the position vector of grey wolves. The vector $\vec{A}$ and $\vec{C}$ is; $\vec{D}$ shows the 2-Dimensional position of the possible neighbours.

$$\vec{A} = 2\vec{a}.\ \vec{r_1} - \vec{a} \tag{3}$$

$$\vec{C} = 2.\vec{r_2} \tag{4}$$

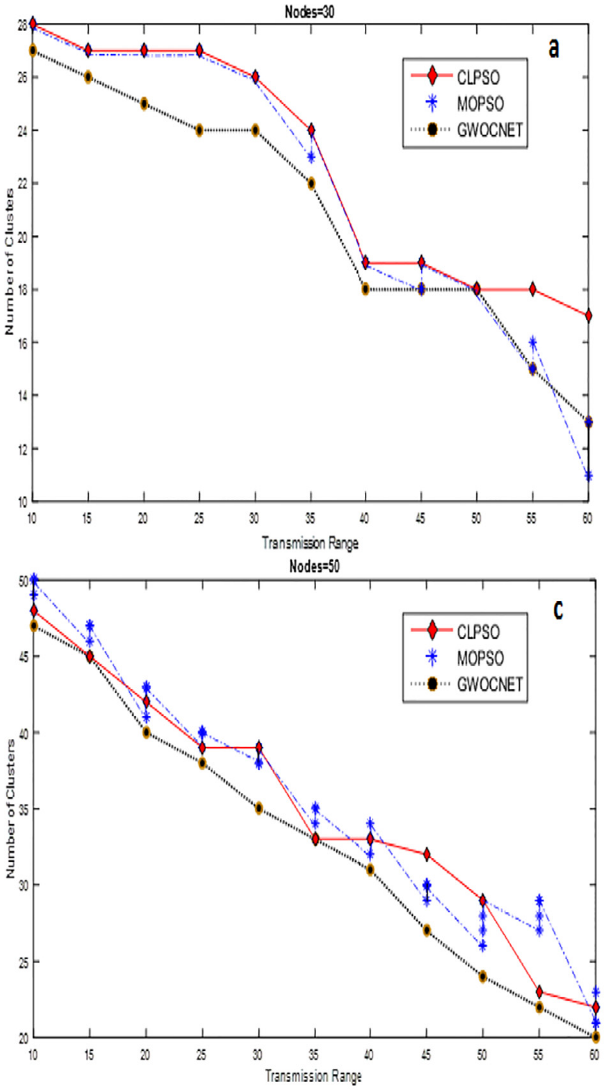

Fig. 7. Number of clusters vs. transmission range in case of CLPSO, MOPSO and GWOCNETs in 400 m × 400 km grid size by fixing nodes from 30 to 60.

In Eqs. (3) and (4), $\overrightarrow{r1}$ and $\overrightarrow{r2}$ are random vector range from 0 to 1. Whereas $\vec{a}$ is the factor which linearly decrease from 2 to 0. Eqs. (1) and (2) is used to update the position of wolves from current location to new-location.

The two dimensional position of grey wolf is shown in [25], with respect to the prey. If wolf is at position (X, Y) and prey at (X^*, Y^*). The grey wolf will update its position according to the movement of prey which is mathematically modelled as in Eqs. (3) and (4). The positions are adjusted with the help of vectors $\vec{A}$ and $\vec{C}$. Same as 3-D position or model is also shown in [25] if the wolf is at any position (X, Y, Z) and prey at (X^*, Y^*, Z^*) any of the position in 3-D so wolf will update their new position of random vectors $\vec{r_1}$ and $\vec{r_2}$.

3.3. Hunting

These wolves try to find the location of optimum (prey) and encircle it for the hunting. Alpha are the senior most or most strengthen wolves in the whole pack designates for the hunting. Sometime betas and deltas also perform this (hunting) task. In mathematical stimulation we store the best three solutions and convey it to remaining wolves (Omega) for updating their position accordingly. These tasks are performed with the help of following equations

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}\right| \tag{5}$$

$$\overrightarrow{D_\beta} = \left|\overrightarrow{C_1}.\overrightarrow{X_\beta} - \vec{X}\right| \tag{6}$$

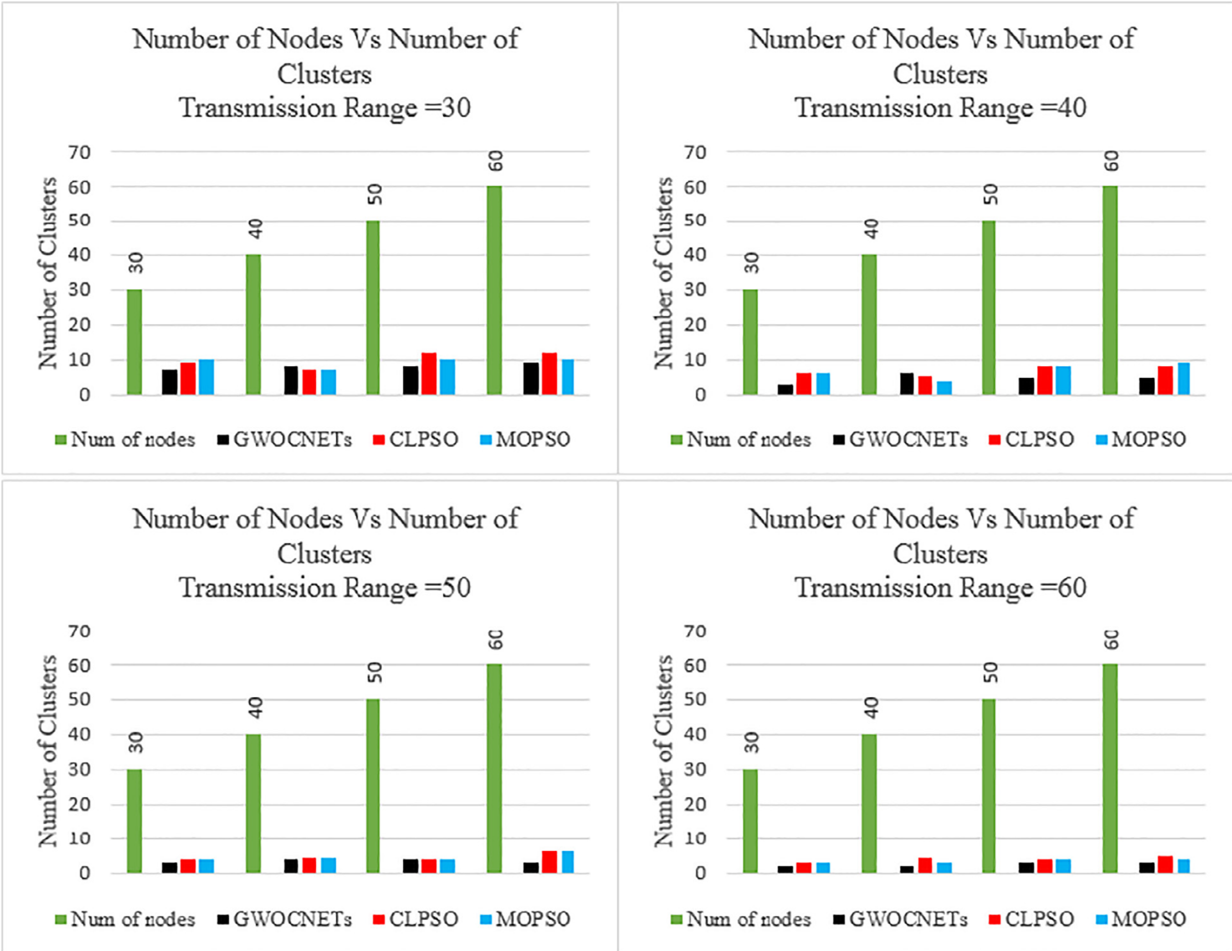

Fig. 8. Network nodes vs. number of clusters in GWOCNET, MOPSO and CLPSO in 100 m × 100 m grid size with transmission range varying from 30 m to 60 m.

$$\vec{D_\delta} = \left|\vec{C_1}.\vec{X_\delta} - \vec{X}\right| \tag{7}$$

$$\vec{X_1} = \vec{X_\alpha} - \vec{A_1}.\left(\vec{D_\alpha}\right) \tag{8}$$

$$\vec{X_2} = \vec{X_\beta} - \vec{A_2}.\left(\vec{D_\beta}\right) \tag{9}$$

$$\vec{X_3} = \vec{X_\delta} - \vec{A_3}.\left(\vec{D_\delta}\right) \tag{10}$$

$$\vec{X}(t+1) = \frac{\overrightarrow{(X_1} + \vec{X_2} + \vec{X_3})}{3} \tag{11}$$

3.4. Attacking prey (Exploitation)

After encircling and harassing the prey, grey wolves attacks the prey when it stops moving. We modelled it in mathematical equations by taking the value of $\vec{a}$. As, change in $\vec{A}$ also reduce the value of $\vec{a}$. The value of $\vec{a}$ is between 2 to 0. In other words if the value of $|A| < 1$, it enforces the wolf pack to attack the optimum (prey). Moreover, if value of $|A| > 1$, this enforces grey wolves to explore more area instead of exploitation.

$$a = 2 - 1*\left[\frac{2}{Max_{iter}}\right] \tag{12}$$

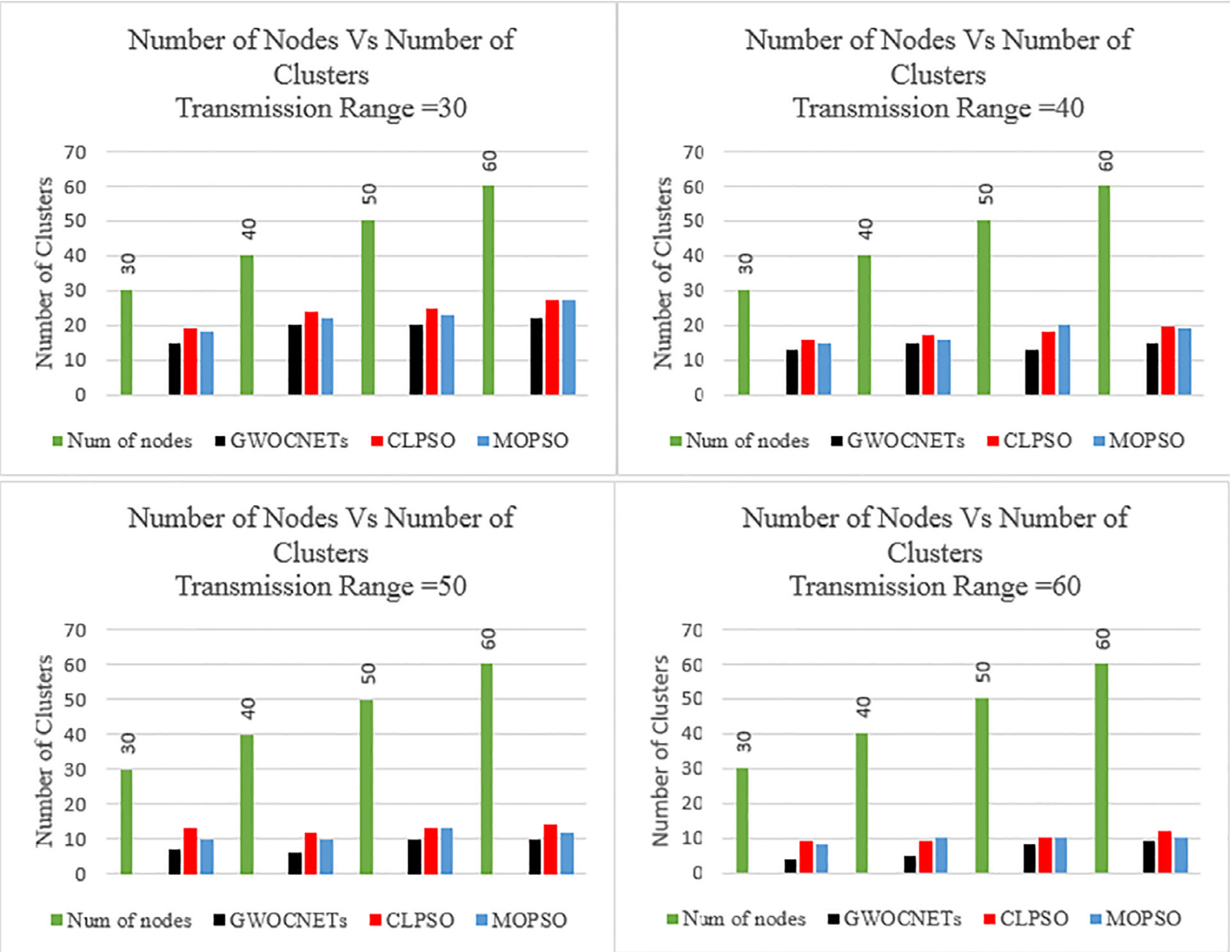

Fig. 9. Network nodes vs. number of clusters in GWOCNET, MOPSO and CLPSO in 200 m × 200 m grid size with transmission range varying from 30 m to 60 m.

3.5. Pseudo code for proposed GWOCNET algorithm

The pseudo code for the proposed GWOCNET algorithm is presented in Table 5. Initially the position of the vehicles is started randomly on the highway by providing the 2 or 3-Dimensional direction. Initialize the vehicles with some speed. The solution set is created in search space. Afterwards, the fitness of Grey wolf is measured and used to create cluster. After each iteration the position of vehicles is updated and new fitness values are measured to find the optimized results. The alpha wolf contains the minimum value as it is considered the best solution, followed by beta and delta respectively. Finally the alpha gives us the optimize number of clusters.

The value $\vec{a}$ is very important as it is the linearly decreasing factor. When the value of a reaches to zero it give us the optimize solution. The value of $\vec{A}$ and $\vec{C}$ are also discussed in methodology section in details.

The given Fig. 3, is used to show the different stages or activities during the execution. The nodes are initialized in the network randomly, we create the cluster matrix by finding the neighbours and keeping in mind that only one node should be selected only in one cluster. Moreover, the two objective variable w_1 and w_2 is used to evaluate the cluster matrix. The condition of maximum iteration, which is also the stopping criteria is used. In the next stage the fitness values of search agents are calculated. The linearly decreasing factor is also used to take the execution toward the result. After single iteration the positions of nodes are updated and process continues. At the end, when linearly decreasing factor a moves toward zero, the alpha wolf give us the optimized solution. The number of clusters in this case.

3.6. Search for prey (Exploration)

Searching the prey or exploration is the main task performed by the grey wolf which is dependent on the position of alpha, beta and delta. These wolves spread in the search space for the exploration and then converge to attack the hunt.

Fig. 10. Network nodes vs. number of clusters in GWOCNET, MOPSO and CLPSO in 300 m × 300 m grid size with transmission range varying from 30 m to 60 m.

In mathematics we use $\vec{A}$, values greater than 1 or less than −1 help the grey wolves to move away from the hunt. Due to which it enforce the search agents to explore globally. As mentioned earlier that $|A| > 1$ means search for the better prey. Vector $\vec{C}$ also has range from [0, 2]. If the value of $C < 1$ it deemphasizes and if $C > 1$ it emphasizes prey in defining the distance. The vector $\vec{C}$ helps the optimizer to avoid the local optima and enforce the process of exploration. It is significant to say here that $\vec{C}$ is not linearly reduced according to $\vec{A}$. The value of $\vec{C}$ is assigned intentionally so that it favors the searching of search space in all the iterations (from initial to final) to track the fitter prey. Because there is a possibility that may be fitter solution can be found in final iteration. $\vec{C}$ is also known as the effect of obstacles in the path for finding the prey. Basically these obstacles in the path of approaching forces to search thoroughly and stop from rapidly and handily finding prey. $\vec{C}$ actually assigns the some random weight to the prey so that it will become hard to find by the wolves. The value of $\vec{a}$ also decreases from 2 to 0 so that wolves can be force to attack the prey (exploit) or search the prey for fitter solution (explore). $\vec{A}$ also enforces to converge or diverge from prey as discussed in Section 3.4. At last, this process terminated by end criterion.

4. Experimentations

For the evaluation of GWOCNETs, the simulation parameters setting are shown in Table 6. The results are presented by using the different perspectives like: transmission range, number of nodes and grid size.

4.1. Number of clusters vs. transmission ranges

Experiments were conducted by using the MATLAB for the different grid sizes and then results are compared with the well-known CLPSO and MOPSO. Fig. 4 illustrates that number of cluster are drawn with respect to different transmission

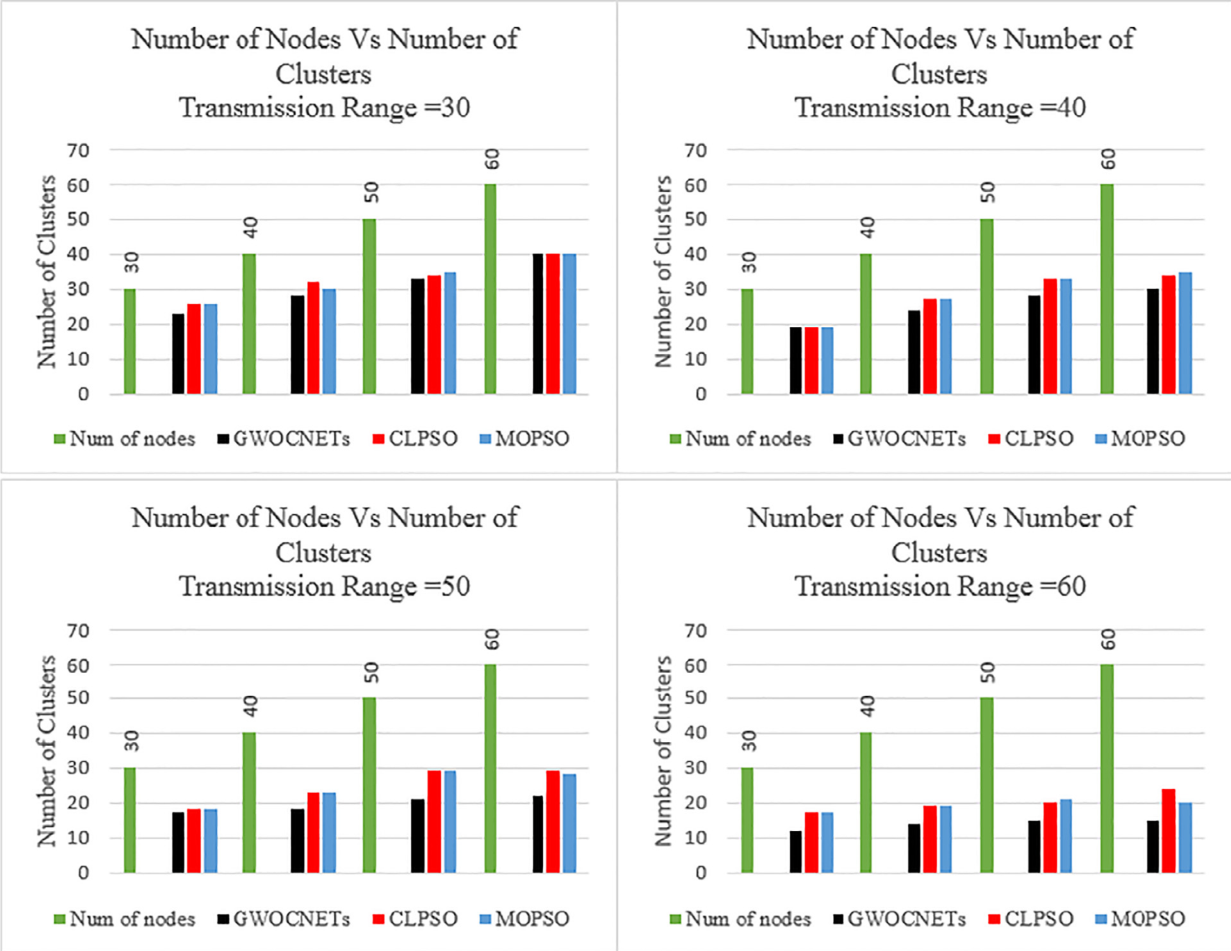

Fig. 11. Network nodes vs. number of clusters in GWOCNET, MOPSO and CLPSO in 400 m × 400 m grid size with transmission range varying from 30 m to 60 m.

ranges from 10 to 60. These graphs are drawn by using the four different numbers of nodes i.e.; 30, 40, 50, and 60. We can easily see that proposed algorithm is showing the minimum cost at the whole graph for all transmission range. Consequently, GWOCNETs based on GWO is also showing the minimized cost for all the mentioned number of nodes (30, 40, 50, and 60). In this graph we have taken the grid size 100 m to 100 m.

Fig. 5 is taken from the experimentation of grid size 200 m by 200 m. This graph also shows that GWOCNETs is cost effective for the communication. There is critical relationship between number of clusters and transmission range. There parameters are inversely proportional to each other. Which mean when we increase the transmission range the number of cluster required for the communication of the entire network decreases and vice versa. There is one more relation between the number of clusters and required resources. Due to reduction in the number of cluster, the resources required for the entire network clustering also decreases.

The grid size of 300 m in length and 300 m in width is taken for the different number of nodes (30–60). The comparative analysis in Fig. 6 shows that GWOCNETs is still showing the better result in the given scenarios. By using the results we can also say that proposed technique will reduce the packet delay and number of hops during the communication in the network. By considering all these factors it will be also reduce the cost of routing. Because when there will be more number of clusters required the resources required will also be more as compare to the less number of clusters.

This is the final scenario implemented to show the fallouts of GWOCNETs with the comparison of CLPSO and MOPSO. Fig. 7 is continuing the sequence of results that GWOCNETs is significantly optimized that the other mentioned algorithm. These graphs justified the relationship between number of clusters and transmission ranges. Number of clusters required and resources required for the entire network. All this optimization leads to the reduction of routing cost for the entire network.

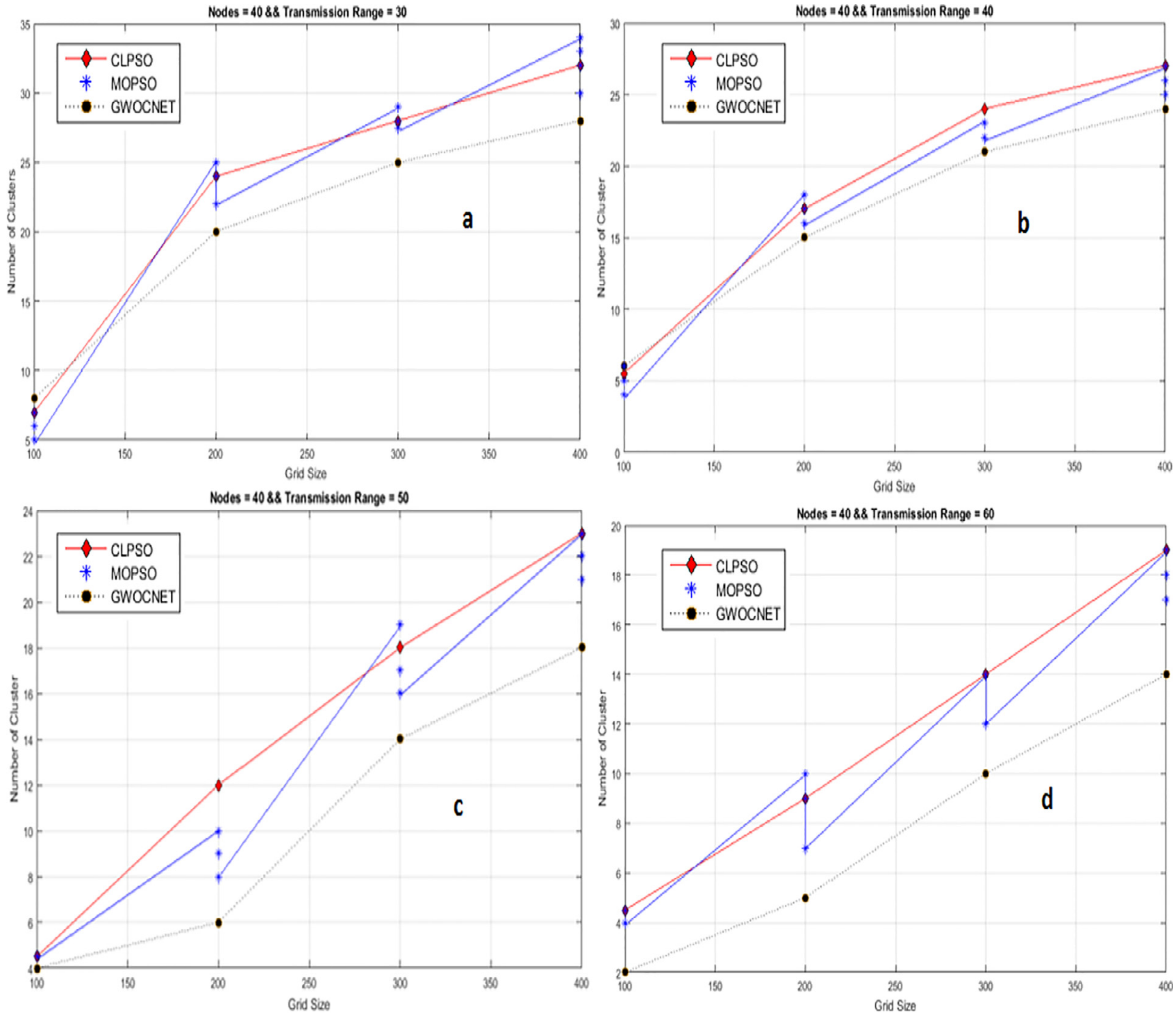

Fig. 12. Number of clusters vs grid size in case of CLPSO, MOPSO and GWOCNET when node = 40 and transmission range varies from 30 to 60.

4.2. Number of cluster vs. number of nodes

To find the corresponding number of nodes in each cluster, experiment is conducted by setting the transmission range as 10, 20, 30, 40, 50 and 60 with the number of nodes varying from 30 to 60. Fig. 8 shows the results against the grid size ranging from 100 m × 100 m to 400 m × 400 m, Fig. 8 shows the attained results by fixing the grid to 100 m × 100 m and changing the transmission range from 30, 40, 50 and 60. It is clear from the experiment that by using the three algorithms MOPSO, CLPSO and GWOCNET, transmission range increases if we decrease the number of clusters by taking nodes keep on increasing and taking the transmission range constant. Number of clusters remains same for GWOCNET as shown in Fig. 8(c). Proposed algorithm shows the flexibility and robustness in terms of metric values and shows better results in a case of average number of clusters in contrast with other algorithms.

Fig. 8(d) clearly shows the GWOCNET made two clusters in start and with the increase in nodes to 60, number of clusters changed to three. Analysis clearly shows the better performance of the GWOCNET in increased load of traffic.

New grid size is taken as 200 m × 200 m as shown in the Fig. 9. After the detail experimentation and analysis it is concluded that GWOCNET has shown better and improved performance with respect to two other algorithm MOPSO and CLPSO.

Increased grid size is taken now to 300 m × 300 m with the transmission range of 30, 40, 50 and 60 and the results are shown in Fig. 10. By comparing the results with Fig. 10, it is evident that on increasing the size of grid, number of clusters also increases showing the direct relation between network size and number of clusters.

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Now the new dimension of grid is taken as 400 m × 400 m with the variable transmission range of 30, 40, 50 and 60. On increasing the grid size, distance between the nodes also increases which show direct relation and consequently a nodes is isolated. If all the nodes are resulted in isolation state then maximum number of clusters should be produced by all algorithms. By comparing the two Fig. 11(a) and (b) it is clear that the two algorithms MOPSO and CLPSO results in same number of clusters whether the proposed algorithm GWOCNET shows better performance and results. 60 nodes are shown in the Fig. 11(d) on the other hand GWOCNET shows 46% less clusters.

4.3. Number of clusters vs. grid size

Relationship between different number of clusters and grid sizes is shown in Fig. 12. As we see the grid dimension to 300 m × 300 m with fixed number of nodes with 30. It is clear from Fig. 12 that the relation between Number of clusters and grid size is inversely proportional, as when we increase the grid size, number of clusters decrease. It is just because in large grid size, nodes are dispersed, hence greater number of cluster are required in order to covet the area. Finally it can be derived that GWONET make less number of clusters as compared to other algorithms.

One of the question arises that at some point GWOCNETs overlap with the results of CLPSO and MOPSO. There is randomness in the nature of evolutionary algorithm so this happens due to the randomness of the algorithm.

5. Conclusion and future work

In the last two decades, various clustering algorithms for VANETs have been proposed in literature, however all of them have some pros and cons with respect to high utilization of wireless resources in the network. The proposed grey wolf clustering based algorithm for vehicular ad-hoc networks is inspired from the daily routine of grey wolves that use four different positions, depicted by α, β, δ and ω to attack the prey. These different wolves are used to perform the operation of exploration and exploitation in the search space. In the proposed method, optimized number of clusters are taken by the convergence of the value of α wolf, as α wolfs reaches to their best value. Simulations are performed in MATLAB and the results are compared with the two variants of Particle Swarm Optimization, CLPSO and MOPSO. Results show that the proposed framework performs better with respect to number of cluster heads with varying transmission ranges, number of nodes and grid sizes as compared to CLPSO and MOPSO. It minimizes the routing cost for the communication of the entire network by efficiently reducing the required number of clusters. Less number of clusters also leads to reduce the resource requirement in the vehicular network. As for the future direction of this work, the process of clustering in VANET can be further investigated by implementing different bio-inspired algorithms like Moth-Flame Optimizer, Salp Swarm Algorithm, Dragon-Fly Optimizer Algorithm, Ant Lion Optimizer and Whale Optimization Algorithm. Moreover, the proposed work can be further enhanced by customizing the objective function as per user requirements, and it can be used for the multi-objective functions as well. The proposed algorithm can also be used for dynamic transmission ranges to vehicular nodes in future.

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