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Moth Flame Clustering Algorithm for Internet of Vehicle (MFCA-IoV)

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ABSTRACT A network of wirelessly connected vehicles by using any mean of connectivity is termed as the Internet of Vehicle (IoV). Managing this type of network is a challenging task. Clustering is a technique to efficiently manage resources in this type of network. In a cluster, all inter/intra cluster communication is managed by a cluster head (CH). Load on each CH, the lifetime of the cluster and the total number of clusters in a network are some parameters to measure the efficiency of the network. In this paper, a novel technique based on moth flame clustering algorithm for IoV (MFCA-IoV) is proposed. Moth flame optimizer is a nature-inspired algorithm. MFCA-IoV generates optimized clusters for robust transmission and is evaluated experimentally with renowned techniques. These techniques are Grey-Wolf-optimization-based method used for the clustering called as GWOCNETs, multi-objective particle-swarm-optimization (MOPSO), clustering algorithm based on Ant colony optimization for vehicular ad-hoc networks termed as CACONET and comprehensive learning particle-swarm-optimization (CLPSO). To assess the comparative efficiency of these algorithms, numerous experiments are performed. The parameters like network grid-size, number of nodes, speed, direction, and transmission-range of the nodes are considered for optimized clustering. The results indicate, MFCA-IoV is showing 73% nodes, which are not selected as a cluster head while existing techniques are providing 57%, 50%, 51%, and 58% for GWOCNETs, CLPSO, MOPSO, and CACONET, respectively. Hence, lesser the nodes are selected as CH, the more optimal result will be considered.

INDEX TERMS Internet of Vehicle (IoV), vehicular ad-hoc networks (VANETs), intelligent transportation system (ITS), Ant-colony-optimization (ACO), particle swarm optimization (PSO), MFO; clustering, meta-heuristic algorithms, population-based algorithm.

I. INTRODUCTION

In computer science and machine learning community, well-known meta-heuristic algorithms like Genetic-Algorithm (GA), PSO and ACO are currently in demand. Particularly, in computer science and in other fields, meta-heuristics are being much inventive and because of high consumption, few questions arise, why meta-heuristic techniques are in demand currently if the comparison is made with other method's. Scientists tried to come up with many logical answers to this question. Few of them include flexibility, deviation-independent method, simplicity and avoidance of local minimum. Due to flexibility of meta-heuristics algorithms, these techniques are well-liked and for solving the problems have contrasting natures. Also, these methods are lenient and provide an easy-going applicability. Since the problem solving techniques of meta-heuristics includes randomness of variables, and most of the time these are deviation-free. It initiates with random solution and excludes mathematical determination of the search-space, while making it suitable for solutions. Meta-heuristics follows the example from daily life routine due to which, its understanding gets easier. To enhance consistency of local solutions, these procedures put emphasis over explorations of the working space. All these characteristics lead the meta-heuristics to solve the NP-hard problems. Therefore these algorithms help to optimize network problems.

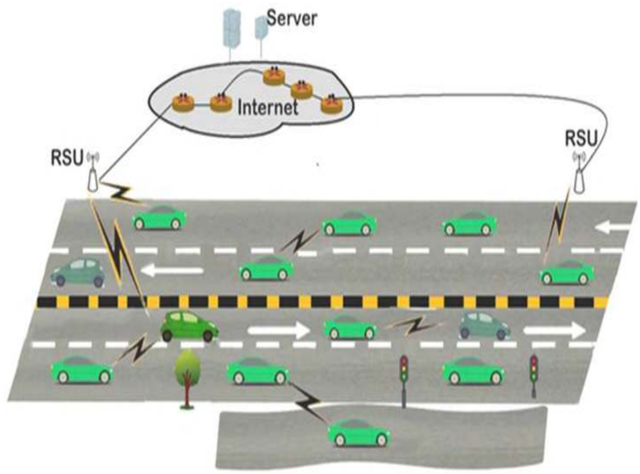

FIGURE 1. **Basic architecture of vehicular ad-hoc networks.**

The simplest definition of network is a collection of devices for communication. Basically, different devices are connected to each other so devices can easily communicate or transmit data to each other. Networks are usually deployed in different domains for specific reasons. One of the environment of network is creating a network for temporal basis. This type of network is called as an Ad-Hoc network. These can be infrastructure less as well as with infrastructure. In Ad-Hoc Networks, there are many sub-divisions such as Vehicular Ad-hoc Networks (VANETs) and Mobile Ad-Hoc networks (MANETs). According to researchers, there will be more than 25 billion things connected with internet by 2020. In 25 billion things a considerable portion is of vehicles that will be connected to form Internet of Vehicle (IoV) as shown in Fig. 1. In VANETs every vehicle acts as a router, mobile node or wireless access point (WAP). The vehicles are connected to each other to form a network. This connectivity allows to perform a communication with in the limited range. There is also a constraint of mobility and density of vehicles in the certain area. There are also few other limitations in VANETs such as large cities, tall buildings, traffic jams, complex road infrastructure and many more. Due to these constraints the VANETs have very limited scope and works in local area.

All these characteristics stagnate the VANETs usage. Therefore, VANETs is moved towards the IoV by considering the two main parameters i-e; vehicles networking and intelligence. Vehicle connectivity is termed as connection between vehicles while intelligence is considered as the combine working of vehicles and drives by using any of the technologies such as; computational intelligence, deep learning, swarm intelligence or artificial intelligence etc. Therefore, IoV is developed for the integration of human intelligence on the vehicle by considering the environmental factors. These factors help the network to execute properly [14]. IoV provides many characteristics such as manageability, credibility and operation ability. IoV also allows to merge with other multiple networks and improves the extensibility, computability and services for managing the large networks. The main idea of IoV is to provide the service to the human for their vehicles up to satisfaction level. It also endorses to provide efficient transportation services for better Quality of Services (QoS). Vehicle telematics are used in automobiles for the complex technologies. Intelligent transportation system (ITS) is the key application of IoV. Now a days, this technology is grooming and growing day-by-day. The concept of ad-hoc is being implemented in different technologies and being used almost everywhere. As the usage of this method is increasing, the demand of new gadgets is also increasing. All this continuous usage and demand make the researchers think about new ideas for better productivity. Nowadays, research work is going on in the environment of IoV for betterment in protocols, communication models and many others. IoV delivers air communication facilities among Vehicle-Vehicle (V2V) and Vehicle-infrastructure (V2I) [15], [16].

The aim is to deliver global and ever-present connectivity to mobile users as they do road traveling [17]. The IoV is now considering growing field in implementation and research as well because many projects are still going on globally for the ITS. In IoV, there are further streams such as V2V, I2V or V2I and last approach is amalgam which is the combination of both mentioned algorithms. Their applications lead to the facilitation in handling traffic jam and many other aspects [18], [19]. It is a potential core of ITS as well which contributes towards increasing traveling people's road safety and advancing transportation efficiency by making use of traffic management. Up till this point in this paper, several routing schemes have been discussed in Vehicular Ad-hoc networks besides the future challenges which are needed for the improvement of these protocols.

But looking for a suitable routing mechanism in urban areas that provides efficient data forwarding and also tends to be suitable enough for ITS applications with polished end-to-end Quality of Service (QoS) is mandatory. Also, when IoV routing protocols are mapped their architecture design must be taken into consideration. In IoV network, nodes inconsistently move, causing structural deviations which result in network separation and due to this, network expires. The lifetime of network is enhanced by predicting the mobility pattern of vehicles. This will result in large-scale commercial use of applications, emergency, safety, multimedia, managing of traffic applications [27]. IoV is the principal framework for ITS. ITS is proposed aiming to design vehicle operations, assist drivers to gather required information for the sake of safety and entertainment, traffic management, and as a source of convenience for travelers. Automatic toll collection and driving assistance systems may be cited as examples. ITS applications generally require numerous messages being transferred via multiple hops between vehicles to move from source to destination. Also, the QoS is another mandatory

TABLE 1. Swarm based intelligent algorithms.

Sr. No.	Algorithm Name	Description	Year of Publication	Reference Number
1	Marriage in Honey-Bees-Optimization-Algorithm (MBO)	Algorithm established for optimization from the concept of mating of honey bees.	2001	(1)
2	Artificial-Fish-Swarm-Algorithm (AFSA)	Motivation taken from the colonial behavior of fish.	2003	(2)
3	Termite Algorithm	Biologically inspired algorithm, resembling the behavior of Termites.	2005	(3)
4	Wasp Swarm Algorithm	Algorithm inspired from the colonial method of living and searching food of wasp.	2007	(4)
5	Monkey Search	Concept taken from the living of monkey. It contain watch-jump process, climb process, and somersault process.	2007	(5)
6	Bee Collecting Pollen (BCP) Algorithm	Developed by the method of collecting pollen by honeybees.	2012	(6)
7	Cuckoo Search (CS)	Logic taken from the cuckoo bird searching method.	2009	(7)
8	Dolphin Partner Optimization (DPO)	A viewpoint of DPO was articulated and a so called "Nucleus" was hosted. It is used to calculate the best position of team member with respect to the fitness values.	2009	(8)
9	Firefly Algorithm (FA)	Flashing behavior of firefly is used to attract the other fireflies.	2010	(9)
10	Bird Mating Optimizer (BMO)	BMO is used for continuous-optimization problems which is extracted by breeding approaches of bird classes during mating season.	2012	(10)
11	Krill Herd (KH)	It is used to form the shepherding of krill for optimization.	2012	(11)
12	Fruit-Fly-Optimization-Algorithm (FOA)	Natural fruit fly foraging behavior is capture in this algorithm.	2012	(12)
13	Soccer League Competition Algorithm	An optimization algorithm to design the water distribution network.	2014	(13)

factor to efficiently transmit data. Delay may become very threatening in situations like safety and surveillance applications. A major problem which does harm to the sustainability of network is named as Scalability. For enhanced lifetime of a network, its load balancing must be managed. Hence, intelligent clustering algorithms significant in this regard for the creation of much optimized [28].

The IoV network which would be a lot more manageable and scalable. Clustering means to group the nodes. These groups are based on similarities and dissimilarities in order to pull off a particular goal in a network. Similarities and dissimilarities may found out by parameters like bandwidth availability, the distance among nodes etc. Clustering also varies from other methods based on some rules. The cluster is made up by a collection of nodes. One node is picked up as a CH. Longer the life of cluster, greater will be the performance of network. Clustering is categorized as NP-hard problem. CH plays vital part in clusters. Some liabilities of CHs include formation of cluster, termination of cluster and resources allocation for the nodes by focusing the factor of network topology for the sake of preservation. Practical-oriented interests have been induced by the favorable outcome of the algorithms? for the past decades. There are speculative research about some properties of evolutionary algorithms forming branch of meta-heuristic, even the theory is obtained by the simulations/experiments. Simultaneously, they look for number of candidate solutions and align fitness value for each of them. Consequently, the best fit is taken as a solution from the number of candidates [29].

Research work is being carried out to improve communication techniques and create a more reliable and safe communication framework for exchanging high priority messages between vehicles. As mentioned earlier, clustering is a beneficial technique for Ad-Hoc networks as well as VANETs and also for IoV. Recently, numerous clustering techniques have been proposed for VANETs and IoV [32], [33]. Most of the proposed algorithms use vehicles mobility features to

TABLE 2. Physics based algorithms.

Sr. No.	Algorithm Name	Description	Year Of Publication	Reference Number
1	Gravitational Local Search (GLSA)	The main features of these heuristics derived from "Newton's law of gravitation", namely a gravitational search algorithm.	2013	(20)
2	Big-Bang-Big-Crunch (BBBC)	The concept of theories for the evolution of the universe is taken to optimize the different NP-hard problems.	2014	(21)
3	Charged System Search(CSS)	An approach taken from the behavior of charges and it is based on the Coulomb law and law of motion.	2010	(22)
4	Central Force Optimization (CFO)	Method develops from the theory of gravitational kinematics.	2007	(23).
5	Artificial Chemical Reaction Optimization Algorithm (ACROA)	The behavior is taken from the nature and occurrences of chemical reactions	2011	(24)
7	Ray Optimization (RO) algorithm	The law for light "Snell's light refraction law" is mapped into an algorithm for solving different problems	2014	(25)
8	Small-World Optimization Algorithm (SWOA)	The concept is taken from the phenomena of small-world and different searching operator's, i-e; small range, large range and random range operators are used in it.	2006	(26)

TABLE 3. Evolutionary algorithms.

Sr. No.	Algorithm Name	Description	Year Of Publication	Reference Number
1	Differential Evolution (DE)	The process of mutation and crossover is used to make the changes in a generation to generation.	1995	(30)
2	Evolutionary Programing (EP)	The finite state machine is developed by different parameters such as alleles, genes and chromosomes	2012	(31)
3	Evolution-Strategy (ES)	The mechanism of evolution and adaptation is used to develop a new method.	2013	(30)

calculate mobility metric between nodes. Mobility metric is used to make clustering decisions such as accepting nodes as cluster members or selecting a node as CH or candidate CH. The most commonly used mobility metrics include relative velocity and distance between two vehicles. Some other protocols use relative acceleration which makes the protocol more applicable to real-world scenarios. There are other cluster membership factors such as packet transmission delay, received signal strength, and link expiration time that can be used based on protocol requirements. In this section, some of the clustering algorithms used for VANET and IoV environments are being introduced and explained. We have categorized the algorithms based on their CH selection criteria. Most of the protocols use the same mobility features to compare mobile nodes. However, the calculated mobility metric and cluster membership rules and CH selection rules are among the distinguishing features of the protocols. The mobility features used by most of the algorithms to calculate their CH selection metric include distance and relative velocity. Some algorithms go further and consider acceleration in their approach, which results in more practical and applicable to real-world protocols as cited earlier.

The main contribution of the research work is a novel technique based on Moth Flame Optimization, called as Moth Flame Clustering Algorithm for IoV (MFCA-IoV). The clustering is the key method to tackle the scalability issue in IoV, the primary contribution of MFCA-IoV is to optimize the clustering process. The utilization of resources for the IoV network is optimized by using the MFCA-IoV. This process is completed by optimizing the number of clusters

TABLE 4. Mathematical modeling of MFCA-IoV.

Task	Mathematical Equation	Equation Number	Description
Moth Initialization	$M = \begin{pmatrix} m_{1,1} & m_{1,2} & m_{1,3} & \cdots & \cdots & m_{1,d} \\ m_{2,1} & m_{2,2} & m_{2,3} & \cdots & \cdots & m_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ m_{n,1} & m_{n,2} & m_{n,3} & \cdots & \cdots & m_{n,d} \end{pmatrix}$ $OM = \begin{bmatrix} OM_1 \\ OM_2 \\ OM_3 \\ \vdots \\ OM_n \end{bmatrix}$	Equation # 1 (a & b)	Here n shows number of Moths and d shows number of dimensions (variables). It is evident that for each moth, fitness function returns a fitness value. First row in the matrix M (position vector) of each moth is delivered to the fitness (objective) function. Output of fitness function is allotted to the relevant moth as its objective function.
Flames Initialization	$F = \begin{pmatrix} F_{1,1} & F_{1,2} & F_{1,3} & \cdots & \cdots & F_{1,d} \\ F_{2,1} & F_{2,2} & F_{2,3} & \cdots & \cdots & F_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ F_{n,1} & F_{n,2} & F_{n,3} & \cdots & \cdots & F_{n,d} \end{pmatrix}$ $OF = \begin{bmatrix} OF_1 \\ OF_2 \\ OF_3 \\ \vdots \\ OF_n \end{bmatrix}$	Equation 2 (a & b)	Here, n indicates number of Moths and d indicates number of dimensions (variables). The subsequent fitness values for all flames are stored in an array.
Three-Tuple Formation	$MFO = (I, P, T)$ $I: \phi \rightarrow \{M, OM\}$ $P: M \rightarrow M$ $T: M \rightarrow \{true, false\}$	Equation # 3 (a, b, c & d)	I is used to create the random population of moths and their fitness value accordingly as shown in equation 3 (b). Whereas, P is used for the movement of moths in the search space. As mentioned in equation 3 (c), it receives the matrix M and returns the updated one. T is used for meeting the termination criterion, if true then terminates otherwise false and does not terminates as shown in equation 3 (d). Algorithm calculates global optimal of optimization problem and is a three-tuple.
General Structure of Algorithm	$M = I();$ **While** T(M) is equal to false $M = P(M);$ **End** $for\ i = 1 : n$ $for\ j = 1 : d$ $M(i, j) = (ub(i) - lb(i)) * rand() + lb(i);$ **end** **end**	Pseudo Code	The function P is recursively executed till the function T returns true. The position of each moth with respect to a flame is updated.
Fitness Function	$OM = FitnessFunction(M)$;	Equation # 4	
Lower and Upper Bounds	$ub = [ub_1, ub_2, ub_3, ub_4 \ldots.., ub_{n-1}, ub_n];$ $lb = [lb_1, lb_2, lb_3, lb_4 \ldots.., lb_{n-1}, lb_n];$	Equation # 5 (a & b)	Here ub defines the upper bounds and lb shows the lower bounds of the variables:
Mathematical Model	$M_i = S(M_i, F_j)$	Equation # 6	Here M_i, indicates the i-th moth, F_j indicates the j-th flame, and S is the spiral function.

with the support of various parameters for different scenarios. Lastly, the comparative analysis is used to show the results of MFCA-IoV and existing schemes.

The paper is further divided into six sections. The literature review is given in Section II, Section III contains the brief description of existing schemes. Subsequently in

Algorithm 1 Pseudo Code MFCA-IoV

```
All vehicles position is randomly initialized on the highway.
The direction of each vehicle is initialized randomly.
Speed/velocity of each vehicle is initialized.
A mesh topology is generated between the nodes, while a vehicle ID is represented by each vertex.
The distance of each vehicle is calculated from one another, normalize and link these values with the resultant edges in the mesh topology.
Create a search-space by initializing the position of Moths.
for i = 1:n do
  for i = 1:d do
    Moth_pos (i, j) = (ub(i) _ lb(i)) / rand() + lb(i);
  end for
end for
while (Iteration == Maximum Iteration or when the solution for previous 15 iteration are same i-e stall iteration ==15) do
  for Mothi = 1 to swarm size do
    Calculate the fitness value against each Moths Position
    MothFitness = CostFunction(Moth_pos);
    Mothi.noOfclusters == empty
    Mothi.Clusterfitnes == infinity
    noOfnodeSelected = 0 (means all the nodes available for clustering )
    while Nodes available for clustering!= 0 or empty do
    end while
    Mothi.Clusterfitnes = CostFunction(Mothi.noOfClusters)
    if Mothi.clusterfitnes < BestSol.clusterfitnes BestSol = Mothi; then
    end if
  end for
  Fitness_sorted = sort(MothFitness);
  sorted_population= F = sort (Moth_position (Fitness_sorted));
  Update the position_best_flame obtained so far
 a)   Best-flame-score=fitness-sorted(1);
 b)   Best-flame_pos=sorted-population (1, :);
  Update the position-moth according to its corresponding flame.
  for i = 1: n do
    for j = 1: d  do
 a)        Calculate Distance of the i-th Moth for the j-th flame using.
 b)        Distance-to-flame=abs(sorted-population(i,j)-Moth-pos(i,j)).
 c)        Update Moth_pos(i,j) update the position of moth.
    end for
  end for
  if (Convergence curve(Iteration)== Convergence_curve(Iteration-1)) then
 a)      stall iteration++;
else
 a)      stall iteration = 0;
  end if
  Iteration ++;
end while
TottalnoOfCluster = BestSol.noOfClusters;
```

Section IV the proposed methodology of the algorithm in detailed. Furthermore, the experimentations are discussed in Section V and in the last Section VI contains the conclusion.

II. LITERATURE REVIEW

Two partitions of meta-heuristics include population-based. It is done by reproducing haphazard assemblage of solutions. For effective output explorations of working space are

TABLE 5. Numerical analysis.

Algorithms	Grid Sizes				Average Nodes Selected as CHs	Average Nodes Selected as CMs
MFCA-IoV	13.03%	24.65%	33.23%	37.42%	27.08%	72.92%
GWOCNETs	19.09%	40.15%	47.47%	61.62%	42.08%	57.92%
CLPSO	24.95%	48.33%	54.29%	68.59%	49.04%	50.96%
MOPSO	5.05%	46.97%	51.72%	68.84%	48.14%	51.86%
CACONET	14.09%	31.01%	45.15%	77.22%	41.87%	58.13%

provided for reduction of stagnation of local solution. Afterwards one solution can generate a candidate which betters their characteristics by increasing iterations. It implies that solution is revised iteration after iteration. Meta-Heuristics algorithms can be categorized into three main branches:

A. SWARM-INTELLIGENCE (SI) ALGORITHMS

SI encompasses several diverse ranges of common algorithms like ACO proposed by Dorigo *et al.* [34]. ACO works over the idea that is extracted from the regular routine of ants. Ant lives together in a colony and searches the nourishment all together. They prefer to discover the shortest and optimal path in order to search for food. Pheromone is a fluid that is released by ant while moving. By computing the amount of pheromone, other ants estimate the shortest path for reaching the target. Particle SI (PSO) has been proposed by Kennedy [35] in which behavior of birds is implemented to find solutions as birds live in a pack and look out for food in a pack maintaining their local best (lbest), personal best (pbest) and global best (gbest). Few SI methods are mentioned in table 1.

B. 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 behaviors of natural phenomena [36]. Some of the physics-based optimization algorithms are laid down in table 2.

C. EVOLUTIONARY ALGORITHMS

The theme of the evolution of nature is being used in this method for problem solving. One of the widely known bio-inspired algorithms is GA. In this algorithm, the process of crossover and mutation is used. Some of them are described in table 3.

Some of the optimization problems in the networks are solved by following algorithms. Different evolutionary algorithms are also used to solve the economic dispatch problem [37]. The usage of evolutionary algorithms is not only in the domain of network but in other domains as well [38]. Different algorithms are also used with the fuzzy based system to solve the complex problems [39]. Optimization is also becoming very well-used in the different domains of networks to make the performance more efficient [40]. Pareto optimal front is formed by using the multi-objective functions [41]. COCO [42], [43] is also proposed to solve continues optimization problem. Binary Differential Algorithm is used to solve the location problem for Incapacitated facility [44]. Symbiotic Organisms Search (SOS) [45] is used to solve the optimization and engineering design problems. The welded beam problem is also optimized by using the genetic algorithm Grey-Wolf-Algorithm for clustering (GWAC) [46] is used to solve the clustering problem. Chatterjee *et al.* [47] proposed Weighted Clustering Algorithm (WCA) in which the process of picking CH depends on weightage of the node based on the different parameters such as; mobility, transmission-range and power. CLPSO [48], [49] is proposed by Khan et al. based on the PSO, this is implemented in the domain of MANETs. A different number of parameters are taken to show the results, such as mobility model, ideal degree, clusters rate, transmission-range and energy. The different weights are assigned to each parameter according to the user requirements and results are shown in graphical form in the referred paper. Another alternative of PSO is proposed by Shahzad [50] and Ali *et al.* [51] called MOPSO for the domain of MANETs. Erfan *et al.* [52] proposed the novel method for the routing to minimize the total cost for the green house. Total cost contains, generation cost, emission cost of gases, vehicular cost and routing cost. The cost increases with the excess emission of carbon-dioxide from vehicles. This dependent on vehicular condition, speed, distance travel and load on vehicle. In the proposed method a hybrid genetic algorithm (HGA) is first developed and then GA is used obtain the best solution. The results has shown the optimal number of result with in the suitable computational complexity. Tan *et al.* [53] proposed the clustering algorithm TSDEGA for the structural health monitoring. The primary objective of the novel method is based on the increasing the network lifetime by using the battery energy as a metric. The proposed approach has also improved the accuracy with respect to the meet time synchronization in structural health monitoring. Yao *et al.* [54] proposed the two level programming based vehicular route for the emergency scenario. The two level programming is based on GA. Different priority based level are defined in it therefore, resources can be assigned accordingly. The simulation are performed for the three types of scenarios such as;

TABLE 6. Comparison of simulation parameters.

Sr. No.	Parameters	MFCA-IoV	CLPSO	GWOCNETs	MOPSO	CACONET
1	**Population-Size/Particles**	100	100	100	100	100
2	**Maximum-Iterations**	150	150	150	150	150
3	**Inertia-Weight (W)**	0.649	0.649	0.649	0.649	0.649
4	$\mathbf{C_1}^1$	2	2	2	2	2
5	$\mathbf{C_2}^1$	2	2	2	2	2
6	**Simulation area**	100x100m^2, 200x200m^2, 300x300m^2, 400x400m^2	100x100m^2, 200x200m^2, 300x300m^2, 400x400m^2	100x100m^2, 200x200m^2, 300x300m^2, 400x400m^2	100x100m^2, 200x200m^2, 300x300m^2, 400x400m^2	100x100m^2, 200x200m^2, 300x300m^2, 400x400m^2
7	**Lower-Bound (lb)**	-	-	0	-	-
8	**Upper-Bound (ub)**	-	-	100	-	-
9	**Dimensions (Dim)**	-	-	3	-	-
10	**Transmission-range**	100 to 600 m	100 to 600 m	100 to 600 m	100 to 600 m	100 to 600 m
11	**Mobility Models**	Freeway mobility model	Freeway mobility model	Freeway Mobility Model	Freeway mobility model	Freeway mobility model
12	**Simulation runs**	10	10	10	10	10
13	$\mathbf{W_1}$	0.5	0.5	0.5	0.5	0.5
14	$\mathbf{W_2}$	0.5	0.5	0.5	0.5	0.5
15	**Nodes**	30,40,50,60	30,40,50,60	30,40,50,60	30,40,50,60	30,40,50,60
16	**Vehicle's velocity range**	22 m/s - 30 m/s	22 m/s - 30 m/s	22 m/s - 30 m/s	22 m/s - 30 m/s	22 m/s - 30 m/s
17	**Maximum acceleration**	1.5 m/s^2	1.5 m/s^2	1.5 m/s^2	1.5 m/s^2	1.5 m/s^2
18	**Minimum Distance in Vehicles**	2m	2m	-	2m	2m
19	**Maximum Distance in Vehicles**	5m	5m	-	5m	5m
20	**Width of Lane**	50m	50m	-	50m	50m
21	**Number of Lanes**	8	8	8	8	8
22	**Evaporation Rate**	-	-	-	-	0.05

no-signal, priority control strategy, coordinated priority strategy. The coordinated priority has shown the better result than others. Wang *et al.* [55] proposed the energy efficient clustering algorithm for the sink node. The novel clustering scheme is developed called as energy-efficient cluster-based dynamic routes adjustment approach (EECDRA) in which cost of route establishment is reduced for maintaining nearly optimal routes to the latest location of the mobile sinks. This scheme has enhanced the network lifetime and energy efficiency. Wang *et al.* [56] proposed the scheme to solve the hot spot problem for sink node. The clustering scheme based on the meta-heuristics algorithm particle swarm optimization (PSO). The cluster is performed during the routing process in which selection of CH is done by residual energy and position of the nodes. The proposed method has enhanced the network performance by prolonging the network lifetime,

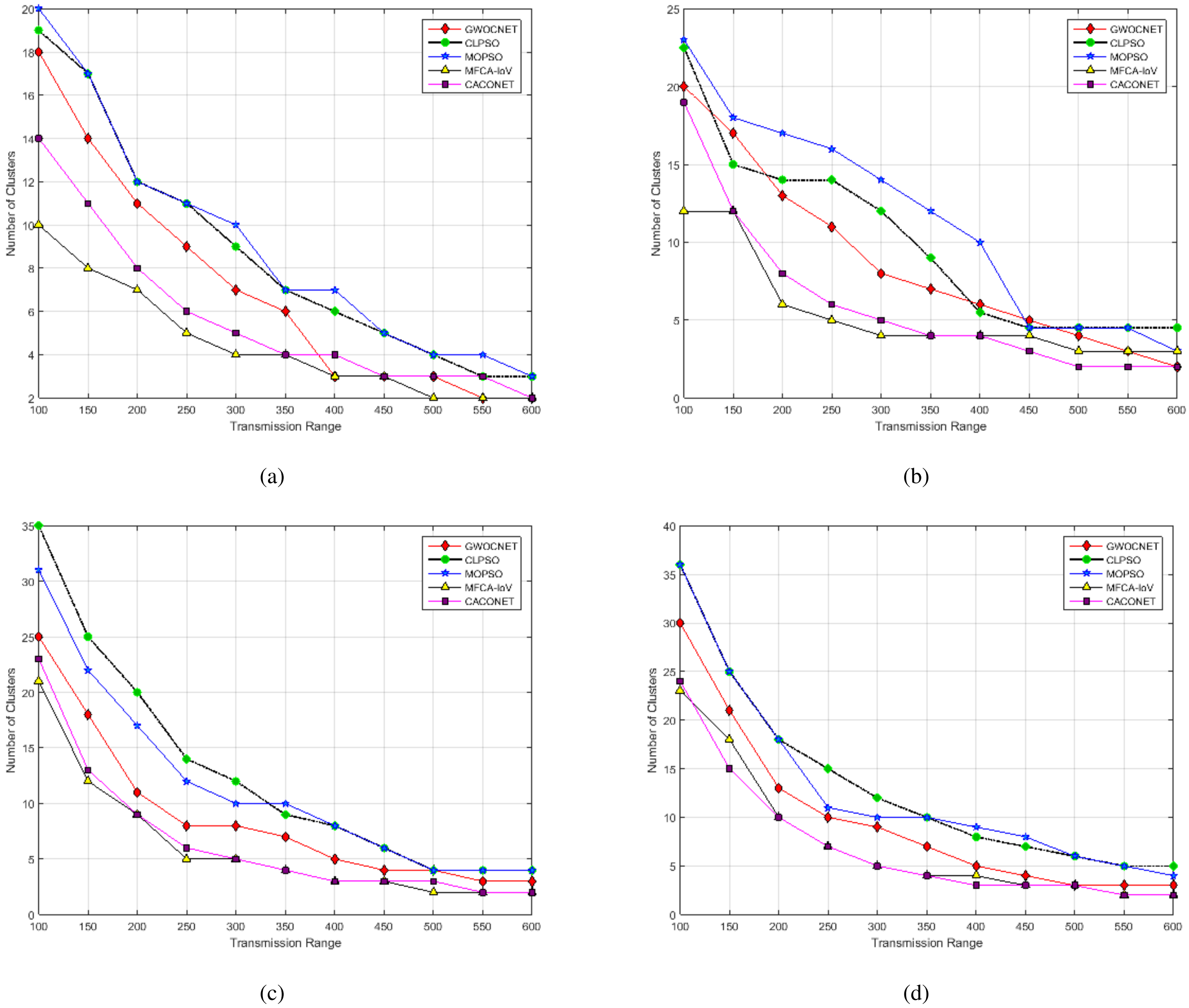

FIGURE 2. Dynamic transmission ranges versus number of clusters with respect to different numbers of nodes for the grid size $1Km^2 \times 1Km^2$. (a) Nodes = 30. (b) Nodes = 40. (c) Nodes = 50. (d) Nodes = 60.

reducing the transmission delay and energy consumption as well. Shankar *et al.* [57] proposed the modified variant of K-mean clustering algorithm to increase the network lifetime by minimizes the energy consumption in WSNs. Modified K-means (MK-means) algorithm chose the three CH at the same time for every cluster. The load sharing method is used in for the transfer of load. This conserves the energy and prolong the lifetime as well. This also help in reducing the re-clustering effect, which ultimately increases the network performance. Shankar *et al.* [58] proposed the energy balancing clustering method to increase the energy efficiency in WSNs. The algorithm is designed by combining the HSA and PSO, it provides the high dynamic capabilities. It enhance the network lifetime by reducing the consumption of residual energy. Potthuri *et al.* [59] proposed the hybrid differential evolution and simulated annealing (DESA) algorithm for clustering algorithm for the energy utilization in WSN. This scheme also focus on the accurate selection of CH, to avoid the network separation and node expiry as well. The proposed framework has reduced the node death rate as compare to other existing methods. Later on, Fahad *et al.* [60] also proposed the CLPSO and MOPSO for the VANETs. More than one solutions are provided as a the result of this algorithm, according to the user nominated parameters. A former variant of this technique provides a single solution and it is insufficient for optimization problems like clustering. Aadil *et al.* [61] proposed the two algorithms COCANET and CAVDO [62], are also the methods in VANETs used for clustering. Ant's colony optimization and Dragon Fly Algorithm conceptualizes these techniques respectively. By making the use of ACONET [63], LBF and complexity is measured in VANETs. For optimization the number-of-clusters in VANETs to obtain the more optimize solution there is a gap of improvement. Oranj *et al.* [64] disagreed over the fact that even if these parameters can be affected by environmental parameters, they usually get ignored, affecting the performance due to throughput. The idea about the identity of each node was proposed by

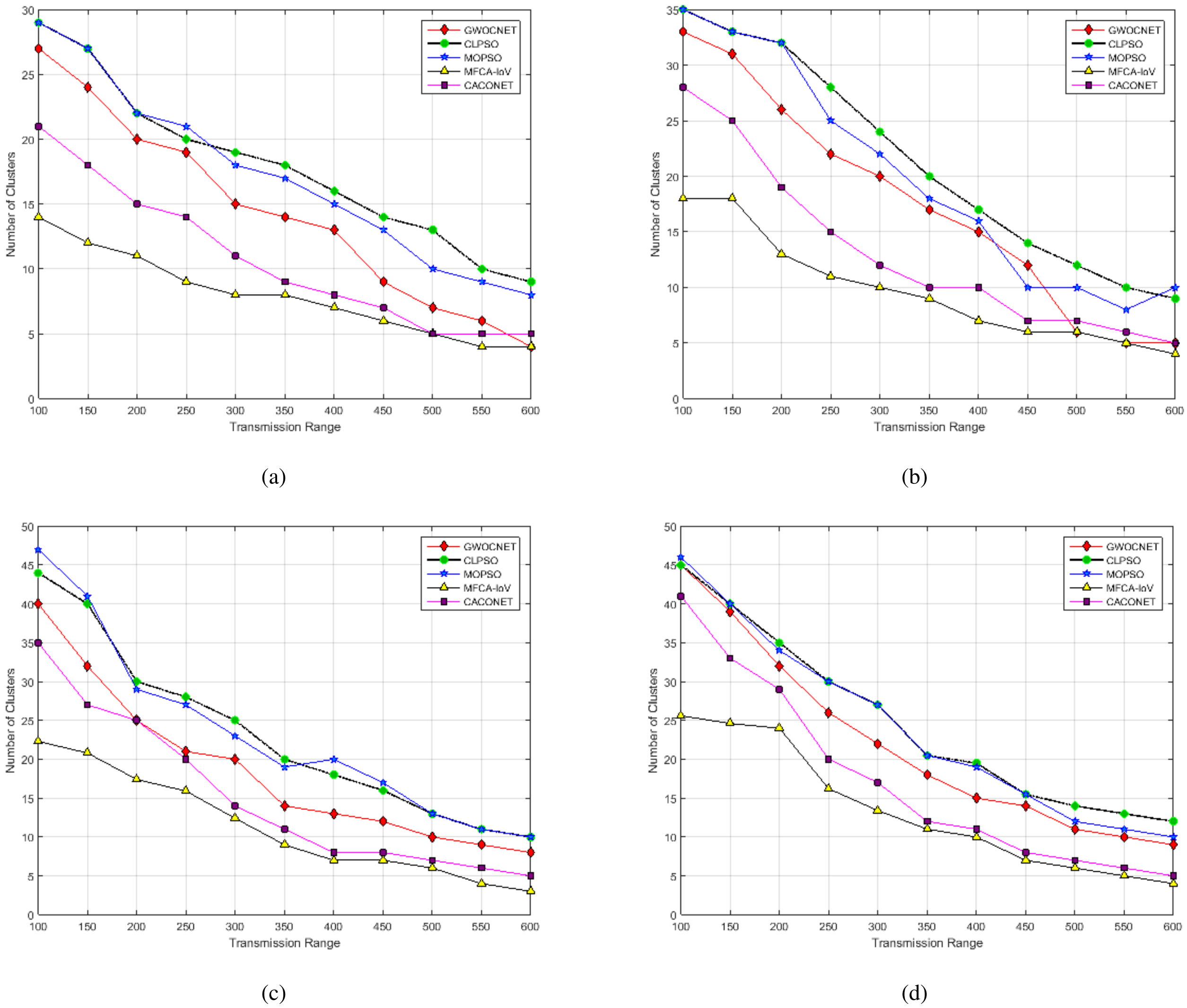

FIGURE 3. **Dynamic transmission ranges versus number of clusters with respect to different numbers of nodes for the grid size $2Km^2 \times 2Km^2$. (a) Nodes = 30. (b) Nodes = 40. (c) Nodes = 50. (d) Nodes = 60.**

Baker and Ephrimides [65] in which, each node contains the unique ID. A node having lowermost ID is picked as CH. Gerla and Tsai [66] anticipated the procedure for the choice of CH by making use of topology-based-clustering where a number of neighbors are computed with each other, termed as node degree. Aadil *et al.* [67] also proposed the algorithm for the flying area network to make the network more optimized for the communication. A node with a higher degree is nominated as CH. MOBIC, a clustering algorithm, works efficiently in the MANETs for picking CH. The ability of network is also weighed by clusters stability which can be assumed in regard to parameters like the ratio of fluctuations of CH and ratio of alteration of cluster nodes to CH. The same problem is solved by the Fahad *et al.* [36], but still there is a research gap which can be improved by using the other meta-heuristics.

III. PROPOSED METHODOLOGY

In the anticipated MFO algorithm, we suppose that possible solutions are Moths and their locations in space are variables of the problem. Moths can fly in 1-Dimensional, 2-Dimensional, 3-Dimensional or hyper dimensional area by changing their positions. As MFO algorithm is a population-based procedure, the set of Moths are presented in the form of the matrix below:

A. MFCA-IoV

Minute bugs named Moths are almost near to the species of butterflies and more than 160,000 diverse kinds are found in nature. Larvae and adult are the two main stages of their lifespan. They have a mechanism of tracking path at night by following moon light. Moth flames fly with respect to the moon by making use of the same angle towards the moon. This mechanism is called transverse orientation and it is used for long path traveling and straight line. This procedure assures that moth will fly in a straight line as the moon is located on immense distance from the moth. Humans can also make use of this routing technique. Suppose an individual who desires to go to the east side and the moon is in the south. If the moon is kept to his left, he can move in a straight line

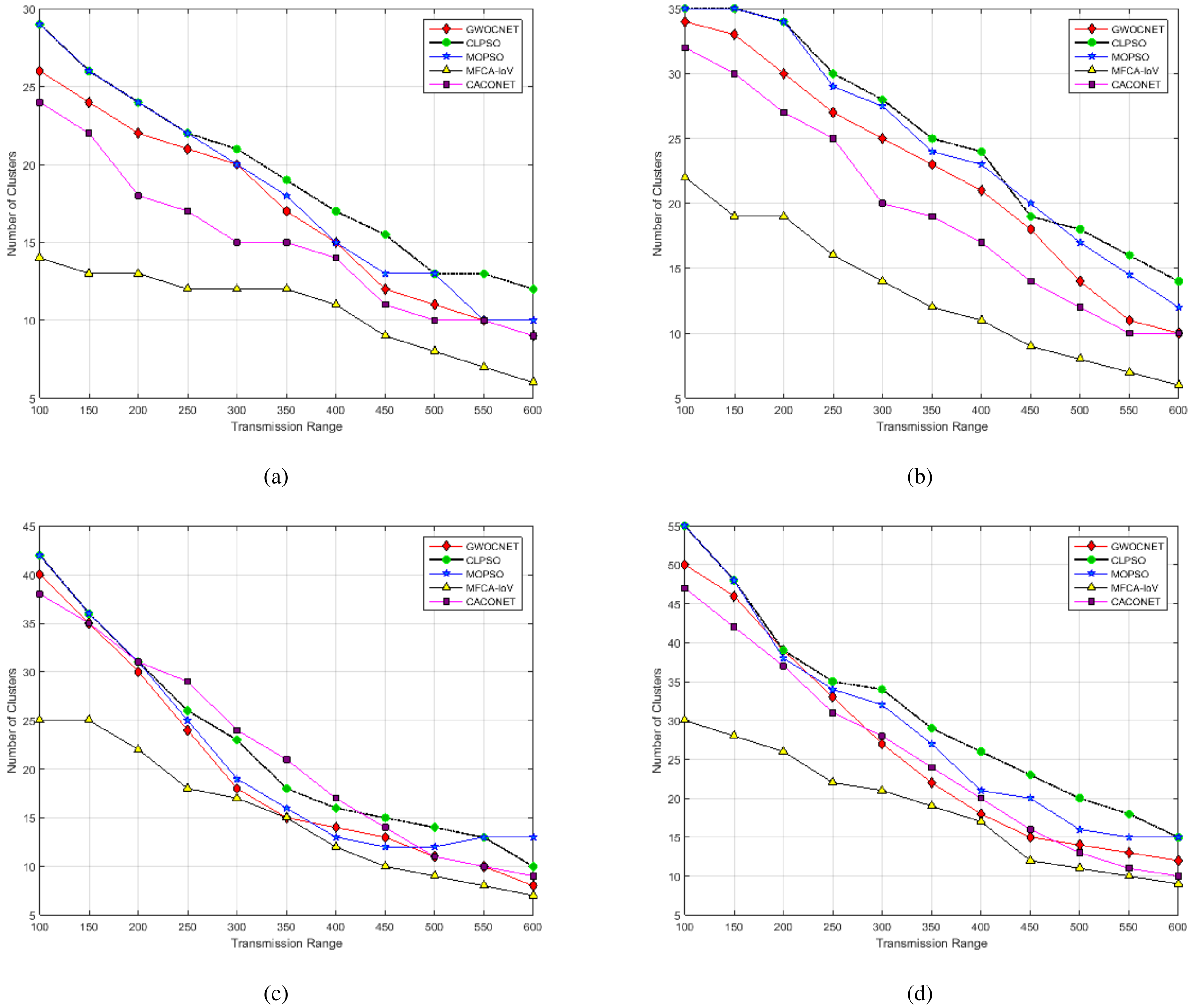

FIGURE 4. **Dynamic transmission ranges versus number of clusters with respect to different numbers of nodes for the grid size 3Km^2 × 3Km^2. (a) Nodes = 30. (b) Nodes = 40. (c) Nodes = 50. (d) Nodes = 60.**

towards the east side. It is frequently witnessed that Moths fly spirally near artificial lights in spite of transverse orientation. Moths can be deceived by man-made lights. Transverse orientation is efficient when the source of light is far away. However, it fails when the source of light is too near [68].

When a man-made artificial light is observed by Moths, they try to retain an analogous angle with the artificial light and move in straight track. But in contrast to the moon, these light sources are exceptionally near. This preserves same angle triggers a lethal spiral trail for Moths [69]. A moth will strike the source of light. In the upcoming subsection, this method is mathematically modeled and MFO algorithm is presented.

B. COMPARED SCHEMES

- It is the primary variant of PSO in which researchers enhanced the working of PSO to get the optimum results Its speed and position are updated [70], [71].
- It is also the variant of PSO in which focus is to get the multi-objectives for the problem so that more than one solution can be obtained accordingly. These swarms are used in multi-objective. Particles update their position and then p-best, l-best and g-best for using them accordingly [48], [49].
- The complete hierarchy of Grey wolf, either male or female, initiates from alpha (α), Beta (β), Delta (δ) and ends at Omega (ω) [72]. The main phases of GWO are four steps performed by Grey wolf from exploration (Tracking, chasing and approaching) to exploitation (attacking) [36].
- As network resources are efficiently and effectively used for the VANETs to make the network more stable. This proposed algorithm is capable enough of optimizing clusters in the network by using the capability of ACO. A single solution is made by an ant and the whole swarm forms the complete solution set [61].

C. MATHEMATICAL MODELING

The mathematical equation of MFCA-IoV is shown in table 4. The next section describes our proposed algorithm

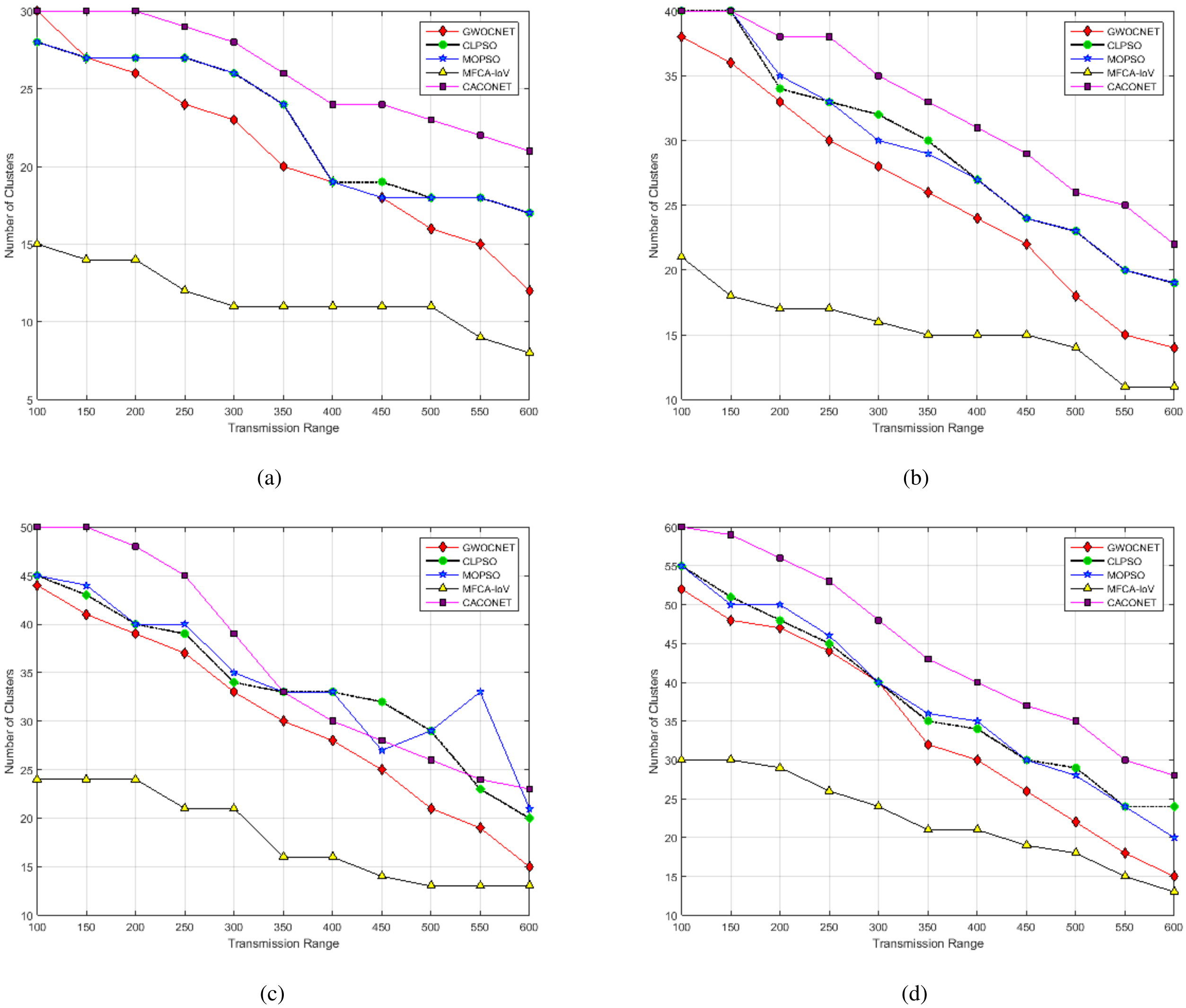

FIGURE 5. Dynamic transmission ranges versus number of clusters with respect to different numbers of nodes for the grid size $4Km^2 \times 4Km^2$. (a) Nodes = 30. (b) Nodes = 40. (c) Nodes = 50. (d) Nodes = 60.

MFCA-IoV which is the first endeavor to accomplish proficient clustering in VANETs by employing MFO algorithm.

D. OBJECTIVE FUNCTIONS

$$f_t = W_1(f_1) + W_2(f_2) \tag{7}$$

where;

$W_1 = W2 \quad = 0.5;$
f_1 and $f_2 \quad =$ objective functions;
$f_1 \quad =$ delta difference
$f_2 \quad =$ summation of the distance values.

These can be calculated by the equation 7.

$$d = \sum_{i=1}^{|t|} ABS\,(D - |CN_i|) \tag{8}$$

$D \quad =$ Ideal Degree;
$d \quad =$ delta difference

d is the difference of calculated number of clusters from the ideal degree. Smaller the value d means less the variation from the ideal degree. It is calculated by using equation 8. This value is dependent on user, for dense environment the value of D will be higher and vice-versa. $|t|$ = Total clusters formation $|CN_i|$ = Number of cluster member; ABS; function used to give absolute value.

Distance between the CH and all of its member nodes can be calculated using equation 8.

$$dist_{CH\_i} = \sum_{j=1}^{|CN_i|} ED(CH_i, CN_{j,i}) \tag{9}$$

ED = Euclidean Distance; CH_i; coordinate position of the ith CH. $CN_{j,i}$; coordinate position of the jth CN.

f_2 objective value is calculated using equation 10.

$$f_2 = \sum_{i=1}^{|t|} dist_{CH\_i} \tag{10}$$

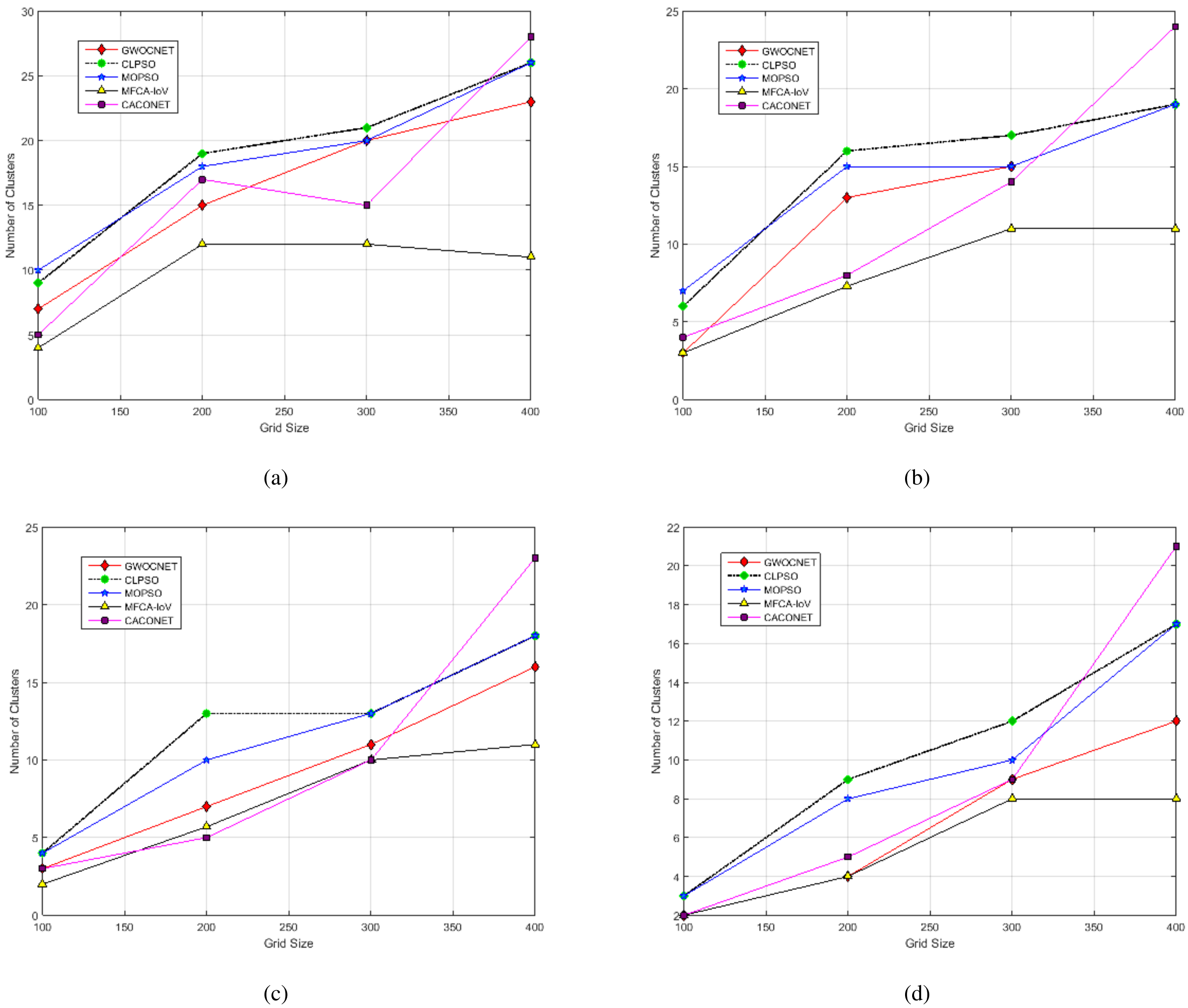

FIGURE 6. Dynamic grid sizes versus number-of-clusters with respect to different transmission ranges for the static nodes = 30. (a) Transmission range = 300. (b) Transmission range = 400. (c) Transmission range = 500. (d) Transmission range = 600.

The shorter the distance between CH and its cluster members, the less the energy will be required to transfer the data as shown in equation 10. In table 5, first column contains the name of compared algorithms. From column two to five, named as grid sizes is used to show the percentage of nodes selected as CHs. For instance in second column grid size $1Km^2$ X $1Km^2$ MFCA-IoV takes 13.03% nodes as a CH while other existing methods take more than the MFCA-IoV. GWOCNETs, CLPSO, MOPSO and CACONET is taking 19.09%, 25.95%, 25.05%, and 14.09% respectively. Sixth column of table shows the average value of nodes selected as CH from all the mentioned grid sizes. As, we can see that MFCA-IoV is consuming the minimum number of percentage in the comparison. Its mean MFCA-IoV requires less number of CHs to perform the robust communication in the network. Meanwhile all other algorithms have required more CHs as shown in table above. In the seventh column of table, comparison is presented with different angle. This column contains the percentage of nodes which are not selected as CH and those nodes remain as CM in the network. The larger value of CM for the discussed scenario of the network shows the better results. MFCA-IoV contains the largest percentage for the number of CM. Therefore, we can say that MFCA-IoV is providing the optimized results as contrast to other mentioned algorithms.

E. COMPUTATIONAL COMPLEXITY

MFCA-IoV Computational Complexity: Following symbols are used in calculations: $n =$ total nodes in the network $s =$ Iterations computed for the clustering $x =$ total flames $j =$ CHs constructed by flame. Computational complexity of MFCA-IoV is computed by considering a each single step and are then merged to accumulate the total complexity.

1) FINDING OF SOLUTION BY A FLAME

In MFCA-IoV for the worst case, $O(n)$ time is required to add a CH in the solution set. For calculating this value probability-based calculation is also performed over moths. For obtaining the best values calculations are performed j times. Therefore, solution obtains is $O(j.n)$.

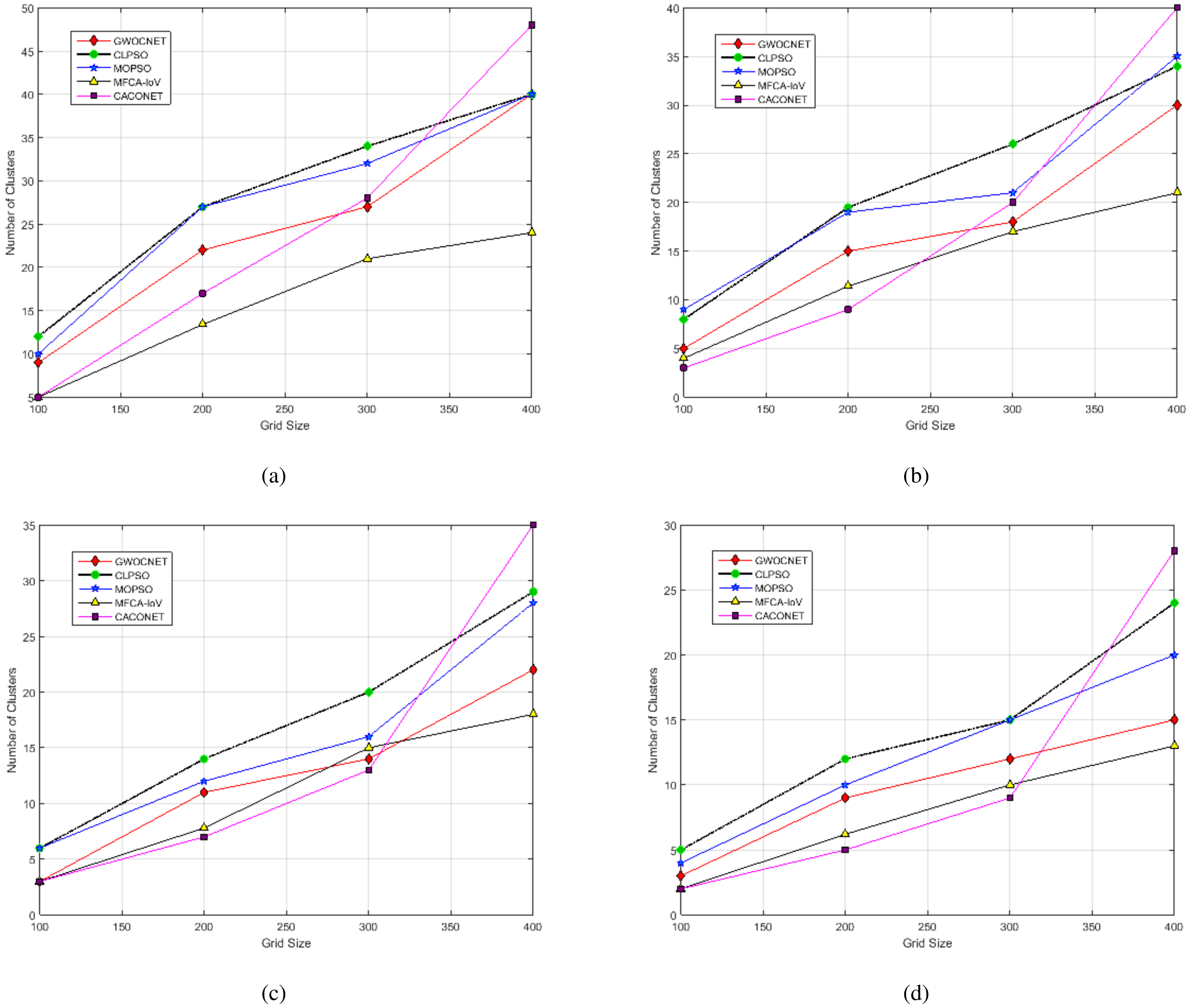

FIGURE 7. Dynamic grid sizes versus number-of-clusters with respect to different transmission ranges for the static nodes = 60. (a) Transmission range = 300. (b) Transmission range = 400. (c) Transmission range = 500. (d) Transmission range = 600.

2) FITNESS QUALITY

It takes $O(j.n)$ time for the calculation of fitness solution due to the presence of j CHs.

3) MOTH UPDATES

$O(j)$ time is taken by MFCA-IoV for updating the moths on the j cluster heads. Since $j \leq n$, so this adds $O(n)$ and its requires $O(n^2)$ for moth updates. MFCA-IoV takes $O(j.n) + O(j.n) + O(n)$ for a flame which breakdowns to $O(j.n)$ and for x flames it becomes $O(x.(j.n))$ So the overall complexity of MFCA-IoV is $O(s.(x.(j.n)) + (n2))$, where n^2 represents the complexity of moths.

IV. EXPERIMENTATIONS

The simulations are performed in MATLAB for the results of MFCA-IoV. Furthermore, the experiments are performed on the system with specifications of core i7 CPU having 2.4 GHz frequency and 8 GB RAM. The results are taken by performing all the experiments for ten times and then average value is extracted to depict the final results.

A. SIMULATION PARAMETERS

Different parameters are taken to run the experiments as shown in table 6; *Results and Discussions:* For the performance evaluation of MFCA-IoV, the different parameters are taken to shows the results. Initially the number of nodes are taken as thirty and it changes up to sixty with respect to the dynamic grid sizes varies from $1Km^2$ to $4Km^2$.

B. NUMBER-OF-CLUSTERS VS. TRANSMISSION-RANGE

In this section, the results of MFCA-IoV, CACONET, CLPSO, MOPSO and GWOCNET are presented in terms of a clusters number and transmission-range. A least clusters numbers represents the improved communication accomplished by technique on any transmission-range. The number-of-clusters are also affects by many parameters in which transmission-range of a node and grid-size plays an important role. If the transmission-range of a node is higher, there will be less number-of-clusters because the more the range of nodes to transmit the data, the more the area will be covered by the nodes. Therefore, the more nodes will be

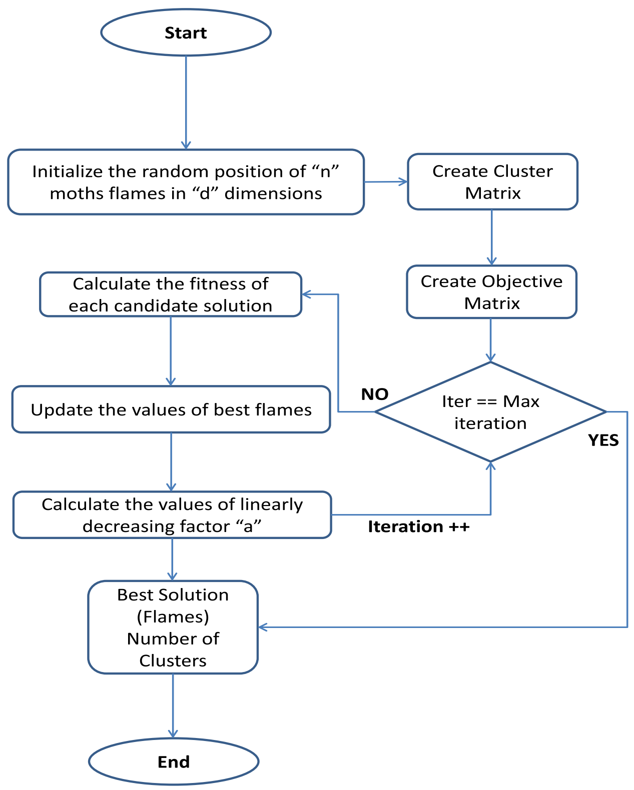

FIGURE 8. Flow chart MFCA-IoV.

accommodated in a cluster. Consequently, it will formed the less clusters. However, by increasing the value of grid-size the more number-of-clusters will be formed for the communication of nodes in a network. By considering the grid sizes dynamically form $1Km^2$ X $1Km^2$ to $4Km^2$ X $4Km^2$, the range to transmit the data of a node is also considered dynamic from 100 m to 600 m. The number of nodes are also changes for getting the different results for different values of parameters.

In Fig. 2,3,4 and 5, a broad association is displayed for MFCA-IoV with number-of-clusters (y-axis) and the transmission-range (x-axis). MFCA-IoV executed better than CACONET, CLPSO, MOPSO and GWOCNET with 30 and 60 nodes density. For higher traffic density, MFCA-IoV is more consistent by constructing the lowest number-of-clusters than other two methods. The impact of transmission-range can be seen in graphs. By increasing the power of transmission the number of cluster will be become minimizing. The range varies from 100 m to 600 m and number-of-clusters are shown on different spots for the different mentioned algorithms. The graphical representation shows that MFCA-IoV is giving the optimized number-of-clusters in almost all the cases. To summarize, all the discussion of results, when transmission-range is high, it results in less number-of-clusters as compare to all the others algorithm. The proposed technique is providing the optimal numbers of clusters which means minimum number of CHs. By reducing the number of CHs, network have to manage the small number-of-clusters. Meanwhile, network will consume the less resources which will result in the better resources utilization of the networks. Consequently, all these factors will lead to increase the network performance.

C. GRID-SIZE VS. NUMBER-OF-CLUSTERS

The results are also shown with another perspective to supports the conclusion. The outcomes are shown in the form of number-of-clusters with respect to the dynamic grid sizes.

The relationship between grid-size and number-of-clusters are shown in Fig. 6 and 7. In Fig. 6, the number of nodes are static, taken as thirty while the transmission-range of vehicles are dynamically varies from 300 m to 600 m. Meanwhile the results with in the different grid sizes differ from $1Km^2$ to $4Km^2$. As, it is depicted in the graphs that MFCA-IoV shows the best results as with the comparison of others algorithms.

Similarly, Fig. 7 is also taken for the static nodes having value of 40, for the dynamic transmission-range varies from 300m to 600m with respect to the different grid sizes of $1Km^2$ to 4 Km^2. It can be seen that even though the number of nodes are greater than the previous scenario but the trend of results is approximately same. Therefore, on the basis of given results and from the second different perspective we can say that proposed methodology leads from the others algorithm and provide the optimized outcomes.

V. CONCLUSION

The ad-hoc is termed as the formation of temporary network. VANETs is a primary branch of it, and there are many challenges in it. The proposed methodology also addresses the one of the problem of IoV. The novel algorithm called as MFCA-IoV is proposed and implemented to solve the robust routing problem by using the clustering techniques. It is observed in the results that MFCA-IoV provides the minimum number-of-clusters with the consideration of different parameters as shown in results. The main parameters include dynamic transmission-range, ideal degree, mobility pattern, dynamic grid sizes, dynamic number of nodes, speed and direction. By considering these factors, MFCA-IoV is providing better results in comparison with well-known algorithms such as; CACONET, CLPSO, MOPSO and GWOCNETs. Furthermore, new algorithms can be implemented to get the better results for mentioned problem.

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