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Clustering-Based Modified Ant Colony Optimizer for Internet of Vehicles (CACOIOV)

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Abstract: The Internet of Vehicles (IoV) has recently become an emerging promising field of research due to the increasing number of vehicles each day. IoV is vehicle communications, which is also a part of the Internet of Things (IoT). Continuous topological changes of vehicular communications are a significant issue in IoV that can affect the change in network scalability, and the shortest routing path. Therefore, organizing efficient and reliable intercommunication routes between vehicular nodes, based on conditions of traffic density is an increasingly challenging issue. For such issues, clustering is one of the solutions, among other routing protocols, such as geocast, topology, and position-based routing. This paper focuses mainly on the scalability and the stability of the topology of IoV. In this study, a novel intelligent system-based algorithm is proposed (CACOIOV), which stabilizes topology by using a metaheuristic clustering algorithm based on the enhancement of Ant Colony Optimization (ACO) in two distinct stages for packet route optimization. Another algorithm, called mobility Dynamic Aware Transmission Range on Local traffic Density (DA-TRLD), is employed together with CACOIOV for the adaptation of transmission range regarding of density in local traffic. The results presented through NS-2 simulations show that the new protocol is superior to both Ad hoc On-demand Distance Vector (AODV) routing and (ACO) protocols based on evaluating routing performance in terms of throughput, packet delivery, and drop ratio, cluster numbers, and average end-to-end delay.

Keywords: ant colony optimization; clustering; 5G wireless networks; routing; internet of vehicles; vehicular ad hoc networks; particle swarm optimization

1. Introduction

Presently, large numbers of industrial and research projects are studying issues related to the energy efficiency of a variety of communication infrastructures. Furthermore, the sophistication of architectures on emerging networks has advanced remarkably and this further increases the necessity for more effective, energy-efficient, and robust infrastructures for network management, while also considering network scalability. Due to existing and future challenges of communication network, a novel promising technology known as the 5G network has emerged to overcome these challenges. Artificial intelligence, Software-Defined Networking (SDN), Self-Organizing Networks (SON), cloud computing, and Network Function Virtualization (NFV) are some of the solutions for integrating the smart communication network [1]. All these efforts contribute to greener and more energy-efficient communication systems and of course sustainability. In this regard, autonomic management capacity on current 5G projects can be improved when faced with network environments that are heterogeneous. Meanwhile, the Internet of Things (IoT) has a significant impact on research areas such as smart health, smart transport, smart industry, and smart homes.

The Internet of Vehicles (IoV) is transforming into a new research area, while relying on a smart transport basis and developing from the Vehicular Adhoc Network (VANET) [2]. VANET follows the principles that govern the Mobile Adhoc Network (MANET) and consists of a wireless network that provides information/communication between vehicles with the use of Dedicated Short-Range Communication (DSRC). The standard of IEEE 802.11a is used for low-overhead operation to IEEE 802.11p [3]. The composition of a VANET is made up of points of access and vehicles, and in the vehicles the major components are the Application Unit and the On-Board Unit (OBU), which is a device used for providing services to the driver, and the application can be located on the OBU or the Road-Side Units (RSU).

IoV consists of vehicles connected to the Internet and other heterogeneous networks, involving a global network of Wireless Access Technology (WAT). The IoV with a heterogeneous architectures network is comprised of 5 distinct communications types. These include the Vehicle-to-Infrastructure (V2I), Vehicle-to-Vehicle (V2V), Vehicle-to-Road-side unit (V2R), Vehicle-to-Sensors (V2S) and Vehicle-to-Personal devices (V2P). The communication architecture of that can be classified into 3 categories: Wireless Access in Vehicular Environments (WAVE)-based ad hoc, hybrid, and Wi-Fi. Each communication vehicle of the IoV, is enabled with the use of a distinctive WAT. This WAT is made up of IEEE WAVE (Wireless Access in Vehicular Environments) for V2V and V2R, 4G/LTE and Wi-Fi for the V2I, MOST/Wi-Fi for the V2S, and CarPaly/NCF for V2P. In Figure 1, the heterogeneous structure of the IoV is shown. The communication architecture is not limited to RSUs and vehicles; however, it can include other communication devices. The complexity and market-oriented nature of the architecture is a result of the inclusion of device ranges, as compared to VANET. The IoV's heterogeneous framework of network vehicles has large potential to supervise and guide vehicles, thus with the capability to offer a platform of communication that is reliable for abundant applications based on multimedia and mobile Internet [2].

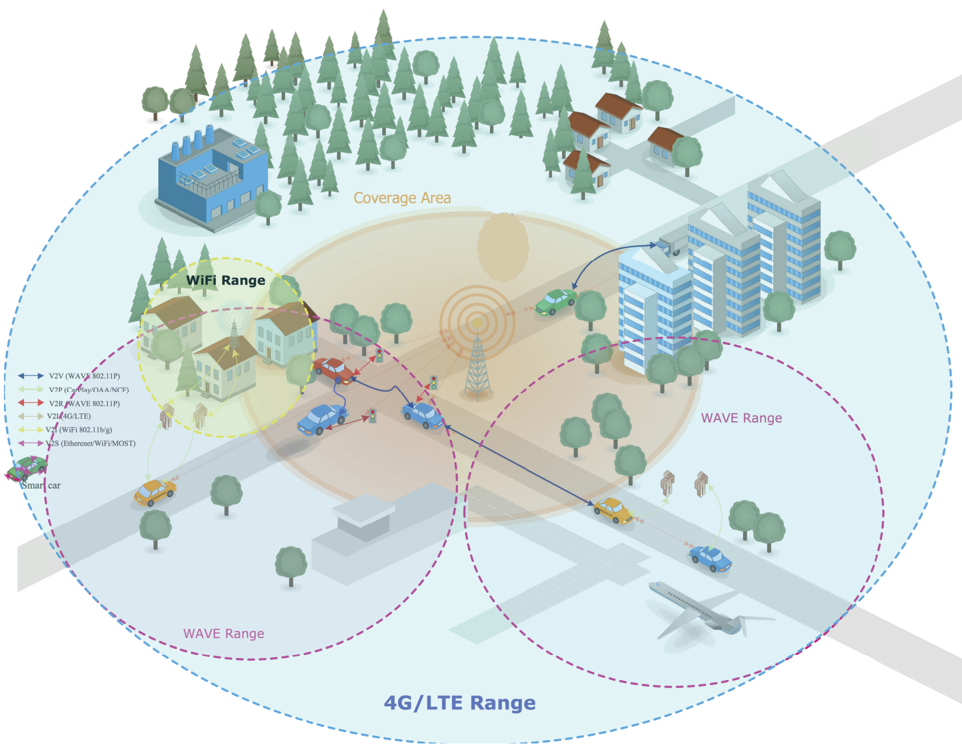

Figure 1. Heterogeneous vehicular networks in IoV.

Moreover, the Intelligent Transportation System (ITS) community holds a consensus that vehicular communications—exclusively VANET—have a positive impact on the efficiency improvement of traffic management and road safety e.g., collision avoidance. Therefore, to establish safe and sustainable mobility, various challenges should be resolved (such as security and connectivity) and contemplated to introduce effective V2X systems to the market that include standardizations, deployment plans, technical challenges, etc. [4]. Technology for routing is a well-known research core of conventional networks. While routing is still a vital aspect of an inter-vehicle network, for VANETs, delivering the control messages is of equal importance [3]. A VANET model has been proposed for highway scenario purposes and it originated from the high-speed movement of vehicles on highways with fewer RSUs than in urban areas.

Now is the proper time to state the general classification of routing protocols for VANET and IoV. Based on the literature, five distinct categories of routing protocols can be mentioned: delay sensitivity; routing in various scenarios' dimensions; transmission strategy, which includes broadcast, geocast, and unicast; information required for performing routing, which includes path-based, position-based, topology-based, and map-based; and routing network types, which includes heterogeneous and homogeneous networks. Since the concern of our study is the IoV environment, the heterogeneous network is addressed. In this regard, clustering algorithms are taken into account. However, this technique classifies them into nine distinct categories, which are mentioned in Figure 2.

While one of the highly important issues for the designers of network is VANET scalability, a model based on clustering is one of the best solutions for such designers of network. VANET communication, which is cluster-based, is affected by the selection of the most appropriate cluster head (CH). When selecting the CH, a consideration of the distance and velocity of the vehicle is necessary for the increment of the stability and efficient message communication in clusters that are intra and inter. To maintain the connectivity of the VANETs, the range of transmission is highly important. If the transmission range is assumed to be static, the network's connectivity is affected and cannot be maintained, due to the non-uniform vehicle distribution and the rapid alterations in the conditions of the networks. Hence, a dynamic transmission range is necessary to sustain the great connectivity in networks that are non-uniform. This issue motivated us to consider dynamic transmission range for each vehicle in the IoV network. Within this aim, we propose a novel algorithm to allocate a dynamic transmission range to each node/vehicle based on local traffic density. Establishment of an appropriate clustering-based nature Ant Colony Optimization (ACO) on the VANET has illustrated successful results [5]. Numerous works have been shown in mobile ad hoc network algorithms based on nature inspiration i.e., swarm intelligence and bio-inspired by insects, as in ACO. This method can be feasible for successfully developing routing algorithms that are efficient.

A temporary network is created from self-configuring nodes, in VANET. This is achieved in the absence of any managements that are centralized or infrastructures that are predefined. Forming a structure of clustering in a VANET environment is one of the means of managing such ad hoc networks. Clustering enables the creation of backbones that are dynamically virtual in a network, aiding the maintenance of the Service Quality in such networks. The experiences of VANET include constrained bandwidth issues and constant changes in topology. Therefore, cluster formation is one of the solutions for managing a network efficiently [5]. Since ideal clustering is a difficult problem in IoV, and is also an NP-hard problem [6], swarm intelligence-based optimization can be used to find near-optimal solutions. By following the principles that are nature-inspired, a swarm-based clustering is made. Such principles can be deduced from bird behavior, genes, and insect behavior. In this context, we can name some well-known algorithm approaches for VANET clustering, such as ACO-based [7,8], the Grey Wolf Optimizer (GWO) [9], and Particle Swarm Optimization (PSO) [10]. To be precise, most of the research in this area is done based on a single-objective problem, learning weights and static ranges of transmission, except for Dragon Fly Algorithm [11].

This study focuses on answering some important questions about routing in a wireless mesh network that are listed below.

- How is the stability of communication in IoV based on the dynamic nature enhanced?
- How is a vehicular network that is more manageable, optimized, and scalable created to have equal distribution of network load?
- How is higher performance achieved in regard to delivery ratio of packet, throughput, and end-to-end delay?

During this research, the aforementioned questions will be answered, the routing protocol's overall performance will be addressed, and the best protocol will be chosen from the two introduced algorithms, which are AODV and ACO.

In real-world application, the node's transmission range is not similar, and the clustering of IoV is multi-objective. Therefore, the dynamic behavior of IoV has propelled this study to develop a modified ACO-based technique. The aim here is to propose a novel framework named CACOIOV to achieve sustainable transportation on the highway with smart mobility via two phases. Firstly, we propose a unique metaheuristic algorithm using an ACO algorithm to select the best vehicles such as CHs, and enhance network stability and provide the most appropriate and shortest routes during V2R communications. The CACOIOV algorithm is developed based on two new ideas: (1) Intelligent first-node selection and (2) Dynamic weight-tuning for pheromone evaporation. Secondly, we propose the DA-TRLD algorithm based on local traffic density to assign dynamic transmission range to each vehicle (Section 3.2). The DA-TRLD algorithm used in the CACOIOV protocol is to maintain the connectivity of IoV network, which is heterogenous and includes non-uniform vehicle distributions. The proposed framework includes different properties: (1) a newness of both algorithms, (2) dynamic parameters of network, and (3) 5G interfacing. For more emphasis, the method which is proposed is built to have multi-objective optimization capacities to have a solution which is more predictable. Our study objective is to provide a routing model to enhance route discovery for vehicles and to maintain network stability in an IoV network. Also, this work can be extended beyond 5G networks and other communication environments such as D2D in future communication. Contributions of our study are described as follows:

- Introduction of a realistic communication model for clustering heterogeneous network that supports V2V and V2I communication.
- Avoiding network dissemination problems, by introducing a novel metaheuristic modified ACO-based clustering algorithm "CACOIOV" to stabilize topology for cluster-based packet route optimization.
- Avoiding the local optimum problem, which is a common problem during route-finding by introducing new approaches in searching space and pheromone evaporation.
- Adapting the dynamic range of transmission in regard to density of local traffic by applying the DA-TRLD algorithm on CACOIOV, ACO, and AODV algorithms to maintain the connectivity of network.
- Contributing to Sustainable Transportation and smart cities by measuring and analyzing the performance of these three routing protocols for the IoV.

The structure of this study is as follows: Section 2 describes the research topic proposed and related works. Section 3 discusses the CACOIOV architecture, proposed DA-TRLD algorithm, and the 5G interfacing of IoV. Section 4 describes the channel models and stimulators. Section 5 illustrates the implementation of the proposed technique along with the outcomes obtained and a discussion about simulation outcomes. In this section, for the purpose of comparative analysis, and better description, mathematical modeling of each segment of the technique, is introduced. Finally, Section 6 provides the conclusion and a discussion of directions for the future.

2. Related Work

2.1. VANETs' Clustering

The challenges in the transition phase of VANET and IoV networks depends greatly on communication security and communication stability in congested traffic. Therefore, VANET connectivity level must be wisely evaluated before real-world application is deployed. Diversity of VANET characteristics has an impact on VANET connectivity level. These characteristics can be named as vehicle/node communication range, vehicle flow and density, traffic lights and RSUs, and the communication equipment's market penetration. Research in this area reveals that with more vehicles equipped with OBU (communicating radios), the enhancement probability of vehicular communication will be increased, which directly leads to higher market penetration and the end result is the improvement of the VANET connectivity level [12].

As mentioned earlier in our study, organizing efficient and reliable intercommunication routes between vehicular nodes based on VANET characteristics is a challenging issue. For such issues, clustering is one of the solutions. The number of changes in clusters ought to be reduced by a good VANET clustering algorithm, which enhances the stability of the network. The other important issues, alongside clustering robustness and connectivity in VANET, include bandwidth, higher link quality to the RSU and the Internet application (i.e., application of Road Vehicle Communications such as a traffic management app, traffic safety app, road monitoring app, and comfort applications such as contextual information and entertainment app, weather information, etc.) that should be taken into account. To facilitate and manage a vehicle user's daily life, the vision of implementing VoIP applications will provide future drivers with the availability to use VoIP services (i.e., Skype, Google Talk, etc.) during congested traffic. Subsequently, the effectiveness of Internet applications is influenced by the routing protocol performance in terms of delay, etc. [13].

There are two classes of algorithms which belong to VANETs' clustering: connectivity-based algorithms and identifier based ones. For the identifier-based ones, the functionality of the node is in the form of the CH if it has the least ID among its neighbors. The connectivity-based clusters, on the other hand, pick a node such as the CH on the condition that the most neighbors are present in the range of transmission. Gerla and Tsai [14] believed a connectivity-based algorithm was not a better option in comparison to the clustering based on identifier. A CBRP algorithm, which is the transformation of the algorithms' lowest ID, was also presented by them [15].

The introduction by Colorni et al. [16] of the ant colony system (ACS) is presented based on outcomes in [17]. This has enlarged the scope of the algorithm's application for resolving various clustering-based issues that have arisen recently. As much as limited studies have been carried out via the use of the data from ACS, the subsequent outcomes have shown proof of the speed and accuracy of the algorithms based on ACS. "Ant Colony Optimization with Different Favor (ACODF)" was introduced by Tsai et al. [18]. This algorithm is made up of favorable ants and the adoption of Stimulated Annealing (SA) to visit the quantity of cities at a reductive rate. Moreover, a strategy of tournament election is engaged to rapidly select a path. The higher trailed intensity nodes are closer in this algorithm, while the farther ones are lower. Thus, visiting the nearby nodes will be preferred by ants and the trail reactivation will be done by ant pheromones. Lastly, construction of the cluster will be made via the division of the pheromone that was laid in between the data point edges. The other variation of the ACS algorithm is presented to cluster data as an ant by Yang et al. [19]. Kuo et al. have made a proposition of two types of clustering algorithms for resolving analysis issues of clustering based on ant K-means (AK) [20] and ant systems (ASCA) [21].

On the other hand, the combination of AK and ASCA are presented in two phases by employing both techniques for database clustering in the first phase and ASCA association rules algorithm is exploited for discovering the rules essential per group in the second phase. The updating pheromone in this algorithm is based on the total within or in accordance to the variance (TWCV) [22]. Sahoo et al. [23], made use of the trust-based method in the routing of ant colony (TACR). Additionally, a cluster algorithm is proposed with the consideration of position, direction, and the vehicle's relative speed for the management of the VANET's scalability. An algorithm for the selection of appropriate CH has been proposed by considering the real-time update of the positions and the value of trusts of the vehicles. The proposed algorithm, based on this research, which was TACR, is compared with the mobility-aware-based algorithm (MAR-DYMO). As a result of the comparison based on routing overhead, TACR has proven to outperform MAR-DYMO. A combined clustering architecture approach and procedures of ACO was introduced by Balaji et al. [24] for VANET efficiency in terms of routing operation in an urban environment. Also, their claim is that the usage of ACO in architectures of cluster is more suitable for VANET. In this context, more literature on VANET clustering is investigated in Table 1. Additionally, the taxonomy of clustering techniques in VANET is illustrated in Figure 2 and in this regard our focus is on intelligence-based clustering protocols.

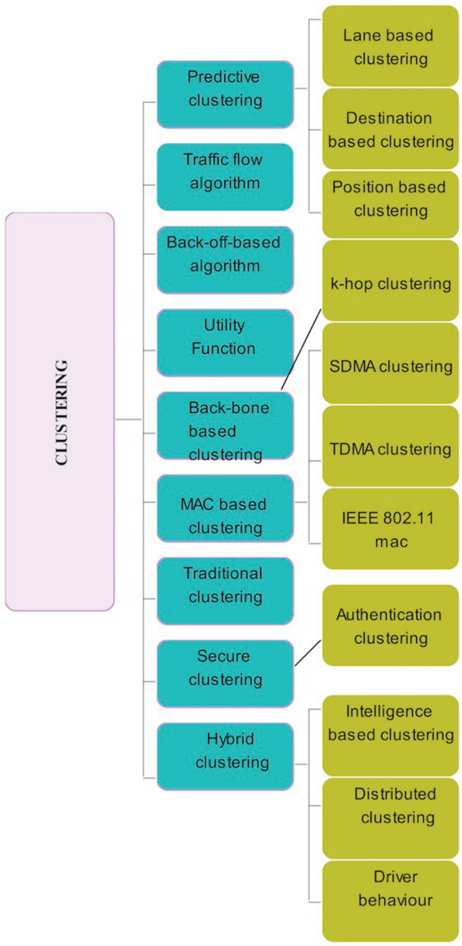

Figure 2. Taxonomy of Clustering Techniques in VANET.

Table 1. Intelligent-based clustering in VANET.

Article	Routing Problem	Methodology	Simulation Model
[25]	Traffic collisions	Bat Algorithm	-
[26]	Unknown true Pareto optimal	Dragonfly algorithm (DA)	Test functions
[27]	Communication disconnections	Firefly algorithm	NS2
[28]	Capacitated Vehicle Routing Problem (CVRP)	'K-GWO' algorithm	MATLAB 2009a
[29]	Rapid topology change	Fuzzy Bacterial Foraging Optimization	NS-2

2.2. Clustering in IoV

A fuzzy system based on logic (FIS) is used in the proposed algorithm of distributed multi-channel and mobility aware cluster-based protocol (DMMAC) to solve the media access issue in hidden terminals for IoVs that were brought forward by [30]. Due to DSRC coverage and a constricted amount of channel communication, a greater opportunity to use the same channel by any node exists. Using FIS sub-channels, this is efficient for this issue, with efficient distribution in the network to curb delays in transmission [30].

The adroit algorithm is introduced for the purpose of efficacious routing in the 5G-cloud-VMesh network (5CVN). On the access layer of 5G, the effectual usage of the source is mentioned by the choosing of a proper gateway of vehicles that are optimal, and aggregator B node (ANB). The performance of the adroit algorithm was well received in performance as well as with the scenarios with respect to other means, although it used only 3 parameters [31]. Mumtaz et al. proposed another 5G and VANET model for Device-to-Device (D2D) communication. For the sake of optimal connectivity, a transmission parameter sensing algorithm is employed considering the resources of D2D spectrum, as these are targeted by sensing algorithms to achieve efficacious connectivity in the D2D environment [32].

The proposition of an SDN-based algorithm on 5G communication is made by Liu [33]. The use of this algorithm is for the management of urban traffic in VANET and for improving repercussion time for emergency circumstances.

Some parameters, such as the localization of the vehicle, traffic prediction mechanisms, and control, are involved in this architecture's method. Chowdhary and Kaur [34] constructed an IoV optimizer algorithm based on dynamic route with the aid of algorithms inspired by nature. Two widely known nature-motivated algorithms, PSO and ACO, are introduced to optimize routing in IoV, while PSO efficiency is less than the ACO, via the provision of longer routes, which require more traveling time.

The method of the removal of the network IP's deficiency network, which is contact centric-based (CCN), is proposed in [35]. Li et al. [36] made a design of the CCN-IoV framework for the CCN methodology in IoV. The performance of this architecture is scale based on the parameters of the network, as in delay and throughput in transmission. This algorithm targeted IoV scalability but is slow for the provision of solutions that are optimal for any proposed scenarios.

The network performance of an algorithm based on ACO for VANET is assessed by comparing the algorithm with two well-known algorithms, which are metaheuristics-based. These algorithms are comprehensive learning particle swarm optimization (CLPSO) and multi-objective particle swarm optimization (MOPSO) [7]. The cost enhancement of packet routing was done by this algorithm, and a number of clusters were minimized, but the weights were still not dynamic. In this method, several parameters of communication, i.e., the range of transmission, pattern of mobility, and topology, are taken into consideration, but are assumed to be uniform for the entire node. On the other hand, having each node with similar range in the network is very unlikely. To conclude, because of the dynamic nature, techniques of evolution can uncover interesting solutions and answers from parametric networks that are larger and non-uniformed.

The dynamic behavior causes evolutionary algorithms to be more synchronized and persistent, to address MOPs. The provision of solution sets, and not just single solutions, explains why the algorithms are built. Several algorithms of evolution are upheld for problems of diverse types, such as the artificial neural network (ANN), the artificial immune system (AIS) [37], the adaptive neuro-fuzzy interface system (AFIS) [38] and the genetic algorithm (GA), which are very popular. Thus, methods based on swarm intelligence are explored for solving MOP problems in the literature [39].

Moreover, lack of robust algorithms that will be able to untangle the challenges faced when tasked with ad hoc wireless multi-hop network routing is also addressed in the literature. In this context, we use promising techniques derived from the sphere of artificial intelligence to overcome this issue. The other gap in existing studies is how a problem that is dynamic, very challenging, and realistic can be solved. In other words, most studies on swarm-based clustering are performed based on single-objective problems that are not appropriate, and are not able to solve dynamic multi-objective problems. In this regard, we proposed a new dynamic algorithm named DA-TRLD, which allocates dynamic transmission range for vehicle communication based on local traffic density to retain the connectivity of IoV network.

Various optimization problems can be solved by ACO, which is a Swarm-Intelligence (SI) technique. This algorithm can be used in finding near-optimal solutions. Even though the ACO algorithm has really strong abilities in solution discovery, search for optimization problems, robustness, easy computer realization, and mechanism of distributed calculation, there are weaknesses such as the longer time for searches, slow speed in terms of convergence, usual stagnation, etc. A lot of researchers have proposed algorithms which are improved for ACO to overcome some shortcoming of ACO. In this regard, our proposed framework improved some drawbacks of the ACO such as uncertain convergence time and random decisions. We listed the pros and cons of the ACO protocol below:

Pros:

- Search can be conducted in parallel among a population.
- It can adapt to changes such as novel distances.
- It discovers good solutions rapidly.
- Convergences are guaranteed.

Cons:

- There is the probability of change in each iteration.
- Difficulty in theoretical analysis and has more experimental basis than theoretical research.
- Random decisions are dependent sequences.
- Uncertain convergence time.

3. Proposed CACOIOV Architecture

In this part of the research, the architecture of the CACOIOV, as well as various mechanisms involved in its framework, are briefly presented. According to the literature, one of the best meta-heuristics is ACO, and the optimization of this algorithm was introduced by Dorigo [40]. ACO is motivated by actual ant behavior and stimulates procedures by real ants to set up the shortest routes for searching food resources. They tend to pick channels that are characterized by the most tenacious concentration of pheromone and heuristic value. The algorithm of the ACO is an important system made based on natural behavior stimulant agents of ants, involving the adaptation and cooperation mechanisms. The ACO algorithm is made up of several iterations (cycles) that are of the construction of solution. In each of the cycles, a number of ants finish up solutions by using investigative information and the obtained experiences by the trail of pheromone, which is kept on the elements constituting a solution. A pheromone can be made on the connections and/or the components employed in an answer considering the problem. Randomly, each ant commences at a node and then pays visits to other ones based on the rule of transition. The process of learning is to repeatedly update the information of the pheromone. Also, ant tour quality can be affected by the evaporation ratio of pheromone (Section 3.2). The quality of ant tour/solution is obtained by calculating the heuristic value over the edges that exist between vertices in each tour. This evolutionary algorithm motivated us to increase the quality of ant tour/solution that results in the shortest path and optimal solutions by developing CACOIOV framework, which is ACO-based. CACOIOV can offer significant improvement in cluster formation. Table 2 presents all notations that are used for analysis.

Table 2. Notations list.

Notation	Definition
V	Networks' nodes
V_{total}	Total nodes in network
TR	Nodes' transmission range-based defined range in standard of DSRC
ΔT_{adj}	Degree of adjustment
T	Maximum iterations
t	Current iteration
D	Degree difference value for Load balancing in ad hoc network = 10
f_1	The delta difference value of the clusters in t
f_2	Summation Distance of CMs from CHs
f_t	Quality of ant tour
w_1,w_2	Equivalent weights assigned to two objective functions f_1 and f_2, respectively = 0.5
ABS	Absolute value
ED	Euclidian Distance
$\|CM_i\|$	Total CMs in cluster
$\|t\|$	Tour length or total number of clusters
$\tau_{ij}(t+1)$	Pheromone trail value encountered in iteration t
ρ	Pheromone evaporation rate
He	Heuristic value
TR_{max}	Maximum transmission range
λ'	Traffic service level of the road $\simeq$ 0.1
α	Traffic constant from traffic flow = 0.25
T_D	Traffic density
T_{TH}	Traffic Threshold
L_D	Local vehicle density
V_N	Number of Detected vehicles' neighbors
d_{front}	Distance between vehicles and it is furthest neighbor in front
d_{back}	Distance between vehicles and it is furthest neighbor behind
NL	Number of roads' Lanes

3.1. IoV's 5G Interface

Frequently, the IoV works with an adherent of ad hoc manner. However, the infrastructural method can sometimes be employed in a scenario where a node lacks a neighbor [41]. In this situation, a semi- or full infrastructure can be employed to ensure a network which is connected fully. VANETs have communication ranges and coverages that are small in comparison to the infrastructure of the 5G. Issues with the IoV include mobility, broadcast of information, and the shortest route paths that can be mentioned in scenarios based on 5G. The 5G interfaces equipping IoVs will adopt additional features in comparison to the conventional IoVs, as well as V2X environments too. The access interface of 5G is made up of resources that are limited, hence having efficacious use of resources user clustering in 5G network are an advantage. 5G has adequate bandwidth for any service types, but desirable use of that is as infrastructure for back-up, since the spectrum of the 5G is paid and has limited channel numbers. Thus, the effectiveness and controlling of 5G access should be observed with algorithms that are dynamic [42]. For the networks that are heterogeneous, different devices communicate with each other with the use of distinctive service types.

Nature-inspired clustering such as swarm intelligence-based algorithms are more reliable than conventional methods. However, these methods require more power of computation, which will affect the energy of the nodes. Hence, the methods are employed on such incidents where the primary issue is not energy consumption. Since OBU is a part of all vehicles in the IoV network and charges easy, energy is not a primary issue for vehicles.

Another aspect of this is that services which are location-based are usually provided by GPS in conventional IoVs. However, in networks with 5G, the management of entities of mobility contains servers of user location which have a connection to the interface of the eNodeB (E-UTRAN Node B/Evolved Node B, which is hardware that enables communication between transceiver station and mobile phone network) access. Therefore, the server of user location can be taken in place of GPS to localize the vehicles' position.

3.2. Protocol Description of CACOIOV

Frequent changes in topology and the increase in mobility need more stable conditions which are improved by reducing the quantity of IoV clusters. A minimum number of clusters indicates better communication in routing-based-clustering due to the shortest path in network. In this study, a unique algorithm, which is the modified ACO enabled with the DA-TRLD, is deployed for efficiency in the CH selection/election to create desirable solutions of clustering for IoV. In methods, which are swarm-based, each node is considered to be a single solution, and the swarm is a group of solutions. An ant, in a given instance, depicts all CH IDs of the entire route. The initial attempt in this work is to create optimum solutions in IoV clustering. Our proposed CACOIOV algorithm by using intelligent first-node selection and dynamic evaporation strategy makes this aim possible. The initialization of the algorithm is made by finding the CHs regarding node speed, distance, direction, and local traffic density by using our novel presented DA-TRLD algorithm and then locating the neighboring nodes of the CHs.

In this research, every vehicle is considered to have interfaces of 5G and 802.11p. The way the vehicular networks are organized is made up of clusters that are managed by the eNodeBs. The cluster sizes are of varying ranges at 802.11p (200–1000 m is the DSRC range for the VANET in highway) based on the vehicular local traffic density, to enable each node to reach the other clusters' nodes, particularly the CHs. The integrity of CACOIOV framework has a methodological scheme involving the following steps that will be explained. The hybridization pseudo-code for CACOIOV and DA-TRLD algorithms can be seen in Algorithm 1.

- Search space modeling and Initialization
- CH selection approaches

Algorithm 1 Proposed CACOIOV algorithm

Creating vehicle traffic on highway by SUMO;
Initialize pheromone and heuristic value on every path Equations (6) and (8);
Creating mesh topology among nodes with DA-TRLD; (Algorithm 2)
Calculating and normalizing Euclidian distance on the mesh topology for corresponding edges;
while Iteration == Maximum Iteration **OR** when the solution for previous 20 iteration are same (e.g., Stall Iteration == 20) **do**
  for $Ant_i = 1$ *to Swarm size* **do**
    Calculate the fitness value for each $Ant_i.tour$
    $Ant_i.noOfclusters$*== empty and* $Ant_i.Clusterfitnes$*== infinity*
    noOfnodeSelected =0 (all nodes available for clustering)
    while *Nodes* available for clustering!= 0 or empty **do**
      $Ant_i.Clusterfitnes$= $CostFunction(Ant_i.noOfclusters)$;
      if $Ant_i.Clusterfitnes < BestSol.Clusterfitnes$ **then**
        $BestSol = Ant_i$;
      EndIf
    EndWhile
  EndFor
  for $Ant_i = 1$ *to Swarm size* **do**
    Evaporate. Equation (11)
    Update Pheromone ($Ant_i.cost$)*. Equation (13)*
    Evaluating Best. Ant.cost;
  EndFor
  if $(Convergence_{curve}(Iteration))$== $Convergence_{curve}(Iteration - 1)$ **then**
    Stall Iteration ++;
  else
    Stall Iteration= 0;
  EndIf
  Iteration ++;
EndWhile
TotalnoOfcluster= BestSol.OfAnt.tour;

Search space modeling and initialization. The algorithm-based solution of the CACOIOV to a particular issue of concern begins with the search space design of a problem. Accordingly, the ants conduct the search to discover the candidate solutions with the graph form. The first step in searching spaces is route initialization which is randomly created by ants before the discovery of the optimal routes. For route initialization some parameters such as direction, distance, number of nodes, and velocity for each ant/vehicle should be initialized in advance. Secondly, WAVE protocol is employed as initialization for the transmission range per node. In this regard, routes are constructed in the form of mesh topology among ants/nodes by using DA-TRLD algorithm.

As presented in Algorithm 2, DA-TRLD algorithm allocates a transmission range for vehicle communication in definite boundaries that are restricted by DSRC in highway scenarios. Our proposed dynamic transmission range algorithm is inspired by following research [11,43]. The uniqueness of the DA-TRLD algorithm is that it considers all vehicles on the highway as a swarm and allocates transmission range for vehicles by calculating the local traffic density of each node. The equations that are used in the DA-TRLD algorithm are illustrated in Equations (1)–(5). The result of this algorithm is used during the process of solution construction (transition rule). As an advantage of DA-TRLD algorithm, we can observe better cluster management by selecting the appropriate vehicle as a CHs in the network. Besides, better network management leads to more traffic congestion facilitation, pollution reduction, and traffic safety. Therefore, drivers can take proper action/make a decision based on the obtained information from awareness of road and traffic conditions. Consequently, driver behavior and driver decision-making directly depends on accuracy of information load that is collected from the existing network.

Algorithm 2 Proposed DA-TRLD algorithm

```
Initialize Traffic service level of the road and Traffic constant from traffic flow;        ([44,45])
Initialize Transmission range based on DSRC standard in the interval of [200–1000 m] for highway;
Initialize Traffic Threshold = 10%;
function DA-TRLD(L_D,T_TH)
    for Ant_i = 1 to Swarm size do
        Calculate Density estimation in vehicle's neighboring by Equation (1)
        Calculate Local vehicle density by Equation (2)
        if Local vehicle density == 0 then
            ΔT_adj = 0
            Calculate Transmission range for Free-flow traffic by Equation (3)
        else if Local vehicle density ⩽ Traffic Threshold then
            ΔT_adj = 1
            Calculate Transmission range for Normal traffic by Equation (4)
        else
            ΔT_adj = 2
            Calculate Transmission range for Congested traffic by Equation (5)
        EndIf
        Return TR
    EndFor
EndFunction
```

The final step in search spaces is pheromone initialization for each ant/node on the graph. In the search space, low values of pheromones are assigned to the edges in the graph that are shown in Equation (6) [7]. This initialization and modeling of search space is illustrated in (line # 1–4) in Algorithm 1.

$$T_D = \frac{V_N}{d_{front}} + d_{back} \cdot NL * 100 \quad (1)$$

$$L_D = [\frac{(1 - T_D)}{\lambda'} + 1]^{-1} \tag{2}$$

$$TR = TR_{max} \tag{3}$$

$$TR = TR_{max} * (1 - L_D) \tag{4}$$

$$TR = \sqrt{\frac{TR_{max} \cdot \ln TR_{max}}{L_D}} + \alpha \cdot TR_{max} \tag{5}$$

$$\tau_{ij}(iter = 1) = \frac{1}{|V_{total}|} \tag{6}$$

Cluster Head (CH) selection approaches. This process includes some steps that are addressed in detail.

(a) Intelligent First-node selection:

A novel way of choosing a first node is inserted in the CACOIOV algorithm, based on a roulette wheel selection for preliminary state of searching space of the graph, rather than randomly selecting the first node which is used in a conventional ACO algorithm. In other words, the first CH in the ant solution is selected 100 percent randomly based on uniform probability $\frac{1}{N}$; but we applied an effective solution for choosing the first node at the ant solution, which can have a significant impact on the quality of ant tour by considering pheromone and heuristic value. In this technique, we inserted an additional column to the pheromone matrix for the first nodes and, based on the worth of solution, the pheromone matrix will be updated and the chance of the first node being re-selected in the next tour as a CH will increase.

(b) Transition rule:

The probability of visiting a vertex by ants that has not been added in a current tour will be calculated with the use of Equation (7). Conducting a solution in the CACOIOV starts in the first ***For*** loop from (line # 6–16) of Algorithm 1. The probability of the vertex being selected as a CH increases due to with the high heuristic (He) and pheromone (τ) values. The edge selection is executed by the selection of a roulette wheel which has low computational complexity as O (1) to prevent algorithms becoming stuck in the local optimum [30]. Since we are using this approach (roulette wheel selection) for constructing a solution (transition rule), therefore, $\tau_{i,j}$ and $He_{i,j}$ are not raised to alpha and beta parameters as in the conventional ACO. The ant tour is finished when two main constraints are applied during the process of vertex selection. The first rule is the vertex, which does not exist in the current tour/solution but can be added into the tour. This rule assures CMs belong to only one cluster. The second rule is any vertex in the transmission range of another vertex in the current solution is not permitted to contribute to the selection process. This rule is to guarantee every cluster has only one CH. The solution construction/selection process will be continued until there are no more vertices available to be added into the tour. Consequently, to decrease the communication overhead, the tours which consist of fewer clusters or CH number will be preferred.

$$P_{i,j} = \frac{\tau_{i,j} \cdot He_{i,j}}{\sum_{k \in s} \tau_{i,j} \cdot He_{i,j}} \tag{7}$$

(c) Fitness Evaluation:

As a result of the multi-objective nature of the clustering of the VANET, the equations that follow are used to evaluate the ant tour by the normalization of the objective function. Equation (8) is used to calculate both heuristic value and objective function [7].

$$f_t = W_1 \cdot f_1 + W_2 \cdot f_2 \tag{8}$$

$$f_1(\Delta difference) = \sum_{i=1}^{|t|} ABS(D - |CM_i|) \tag{9}$$

$$f_2(Dist - sum) = \sum_{i=1}^{|t|}(\sum_{j=1}^{|CM_i|} ED(CH_i, CM_{i,j})) \tag{10}$$

(d) Dynamic Strategy of Evaporation Factor:

The algorithm of conventional ACO consists of static evaporation rate (ρ) with the value of 0.05, which has a direct impact on the convergence rate and capability of global search. Sufficiency of search for ACO algorithm is determined by the evaporation rate, which decreases the pheromone value on an ant tour to zero. If this phenomenon occurs for an unvisited vertex then the ACO algorithm will not be successful in terms of the ability for global search to find the best tour. Hence, tuning evaporating and pheromone value is the controlling key to evaporate and release pheromone. In [43] the aim is establishing a dynamic evaporation rate with a huge value at the start of the ACO process for enhancement ability of the global search. This technique accelerates the convergence to some extent. To explore the decay model better, for the rate of evaporation, there are 3 decay model types: the model of curve decay, scale decay, and line decay. Based on the implementing of a set of experiments, the curve decay is selected by Ping [46].

In this context, we proposed a novel method for finding the effective pheromone evaporation. By considering Dynamic Pheromone Effectiveness (*DPE*) value as zero at the first step, the evaporation rate can be initiated as follows in Equation (11), which is used in (line # 18) of Algorithm 1. Due to the interval evaporation rate, which is [0–1], *DPE* should be multiplied to a constant value of 0.1 ($\rho_{initial}$).

$$\rho(t) = \tau_{ij} * (1 - (DPE \cdot \rho_{initial})) \tag{11}$$

(i) Dynamic Pheromone Effectiveness (DPE):

The other important factor that is suggested by this work is *DPE*. This factor has a critical impact on updating a pheromone and the decision for the next node selection depends directly upon the evaporation rate of ants. This parameter has a change range of [0–1] which changes by time. At first, the coefficient is zero to give adequate time to ants to conduct a better search between existing nodes and, as time passes, this coefficient increases slowly to reach to one. In this regard, the evaporation coefficient of the pheromone is multiplied by the value of pheromone change to balance the convergence speed of algorithm. We computed the *DPE* factor based on Equation (12) when the pheromone-convergence speed is linear.

$$DPE = \begin{cases} min(1, \dfrac{(DP_{CS} * t)}{T}) & \text{if } DP_{CS} > 2, \\ \dfrac{t}{T} & \text{if } DP_{CS} \leq 2. \end{cases} \tag{12}$$

(ii) Dynamic Pheromone-Convergence Speed (DP_{CS}):

We introduced a new factor as DP_{CS} to change the speed of pheromone evaporation. This factor can be changed in a range of [1–$MaxIteration_{ants}$]. By our experiment, if the DP_{CS} value has changed in the range of [1–10], the convergence speed of the algorithm for finding the best solution becomes quicker. On the other hand, increasing this value by more than 10 reduces accuracy for finding the best solution by ants. Therefore, we arranged the changes of this parameter in the mentioned range, not only for speeding up the convergence process but also for achieving the best solution.

(e) Pheromone Update:

To enable the efficiency in the usage of the values of pheromones, the ant tour qualities are employed. The trail quality is updated in each tour based on pheromone values on edges that can be computed by Equation (13). This calculation is used in (line # 19) of Algorithm 1.

$$\tau_{ik}(t+1) = (1-\rho)\tau_{ik}(t) + (1 - \frac{\tau_{ik}(t)}{(1+f_n)}) \tag{13}$$

(f) Solution finding:

After termination of the CACOIOV algorithm based on stopping criteria in (line # 5) of Algorithm 1, the best-found tour is used for advertising the IoV that is $BestAnt_{cost}$ and is determined in (line # 29) of Algorithm 1. Finally, the optimal route will be discovered by the concluding solution for the nodes.

4. Channel Models and Simulator

The method which is employed for the modeling of the wireless signal propagation environment has quite a crucial impact on the protocol performance or the application being evaluated [6]. The simulator, which is the most popular among the ones used in the survey sheets, is $NS-2$ [47]. If the power received for a packet goes beyond a specified threshold, a packet is regarded as having been received successfully, while the noise floor will be constant based on the channel model chosen. The current stable $NS-2$ release is the 2.35 version, involving support for 5 channels: two-ray ground, Friis free-space path loss, Nakagami-M, shadowing based on log-normal, and shadowing based on obstacle. $NS-3$, which is new version of $NS-2$, provides similar channel model sets. The VANET research had most attention on shadowing based on the obstacle to distinguish static objects between source and destination on the direct line-of-sight path. Whether or not such direct paths exist, one of the two alternative shadowing models based on log-normal is configured. A similar approach is followed by this model to the CORNER channel model [48,49], with attempts to make a model of the channel based on specific physical environments in the given node pair's vicinity. Most research is done by using $NS-2$ and choosing channel models such as Nakagami-M, two-ray, or free-space. The simulator distribution used in the validation process of the surveyed algorithms is illustrated in Figure 3 [50].

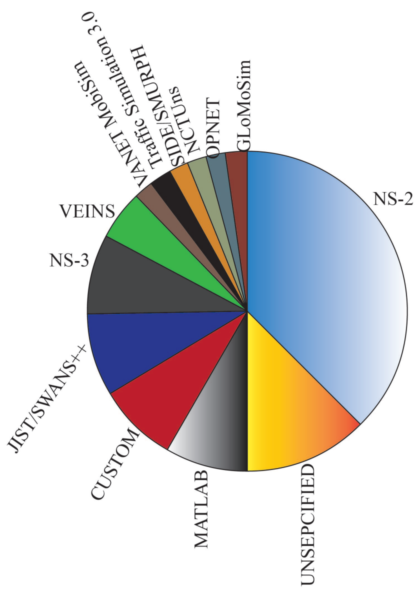

Figure 3. Simulators used in validation of the surveyed algorithms.

5. Evaluation

5.1. Simulation Assumptions

This part of the research presents the metrics and parameters used in simulations. The topology employed in the simulations carried out is two parallel highways (2 × 4 lanes) across the area and eNodeB, which is placed in the middle lane of both directions. The VANET vehicles are equipped with the DRSC, and the positions of vehicles are provided by the location server. Vehicles that move in similar directions in the proposed algorithm are considered to be neighbors. Also, a V2R communication scenario is considered for simulating our idea. The overview of our scenario is presented in Figure 4. The protocol is implemented on NS-2.29, and the vehicle mobility is generated with the usage of SUMO [51]. The WAVE-802.11p protocol is defined as allowing communication among vehicles of high-speed or between a road-side infrastructure network and a vehicle. The metrics of performance used in the assessment of simulation results were packet drop ratio, throughput, end-to-end delay, clusters number and packet delivery ratio versus the increasing number of vehicles in networks size of 4 km^2 in cases where the simulation times is 1000 s and is constant for all changes. The simulation is performed 10 times for all mentioned three algorithms (CACOIOV, ACO, AODV) and the average is used in the result. In both algorithms of CACOIOV and ACO, 150 rounds are considered for artificial ants to achieve the best tour in each of 20 iterations, which indicates criteria for the enhancement in quality of the best tour.

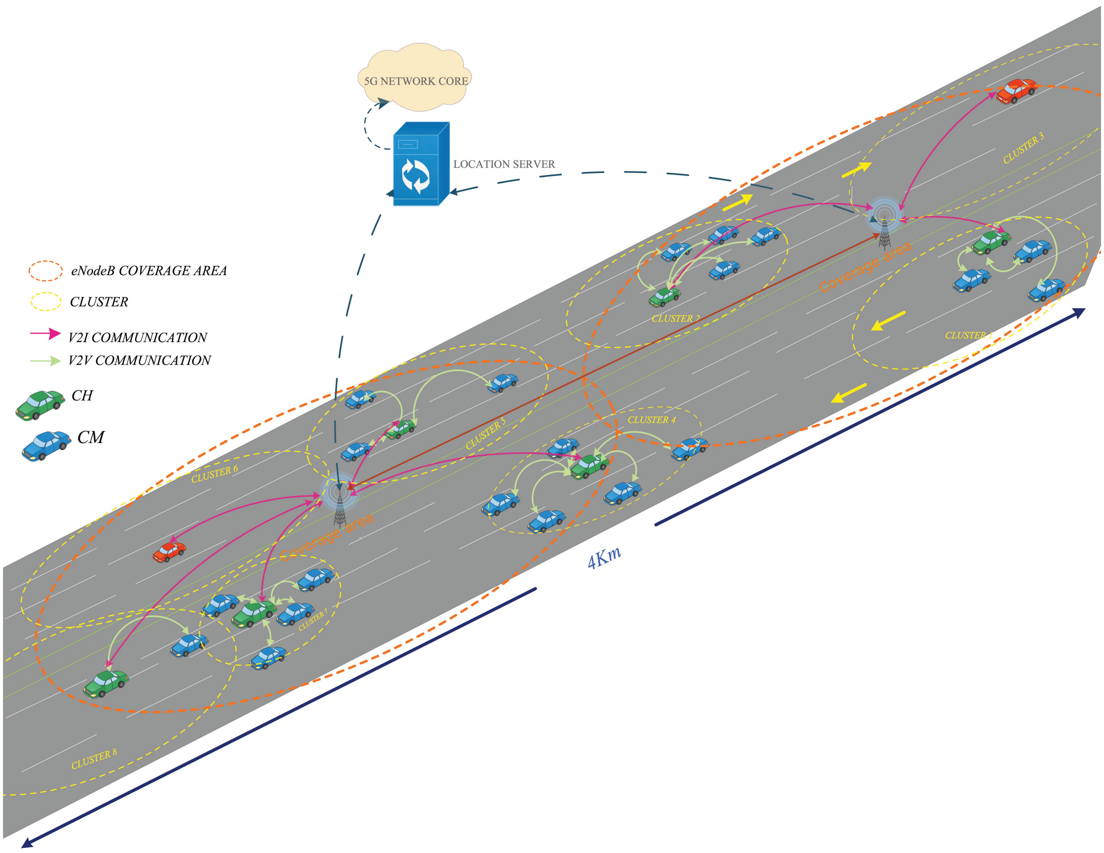

Figure 4. Proposed Scenario.

5.2. Results and Simulation Analysis

The outcomes of the simulation are presented and analyzed in this section, with the provided parameters used from Table 3. The interpretation of experimentations in this study are classified into five different categories for evaluating the performance of CACOIOV, ACO, AODV algorithms. In five different classes, parameters such as throughput, Data Packet Delivery Ratio (DPDR), number of clusters, delay and packet loss are compared for these three algorithms with respect to the number of vehicles in the network. In this regard, we combined our proposed Algorithm 2 which is DA-TRLD with ACO and AODV algorithms to achieve realistic results by making a fair comparison.

Table 3. Simulation Parameter of Protocols CACOIOV, ACO, and AODV.

Parameter	Value
Simulations Tool	NS2, SUMO
Mobility model	Freeway mobility
Radio Propagation model	TwoRayGround
Antenna model	Omni-directional
MAC layer Protocol	WAVE/IEEE 802.11p
Beam-forming technology	MmWave
The maximum size of packet in the queue	Priority queue (50 packets)
Interface Queue Type	Drop TailQueue
Population size (ants)	=number of vehicles
Node movement	Bidirectional
Maximum iterations	150
Grid size	4 km^2
Velocity	22–30 m/s uninform
Number of network nodes	40, 80, 120, 160 and 200 vehicles
Transport layer protocols	UDP
Traffic Type	CBR
Transmission range	Dynamic
Packet size	512 bytes
Simulations run	10
Confidence interval	95 %

- ***Throughput:***

This is the average rate of the data packets transmitted successfully over the IEEE 802.11P/5G communication channels' capacities. Figure 5 shows that the CACOIOV algorithm has better throughput than the other algorithms via a test of all number of vehicles. Besides this, the graph of ACO shows fluctuation of throughput when the number of vehicles increases. Also, by increasing the number of vehicles from 40 to 80, we notice throughput reduction for all these algorithms. Additionally, changing the number of vehicles from 40 to 200 has a negligible decrease on throughput of the CACOIOV scheme. We conclude that throughput will decrease by increasing the number of vehicles.

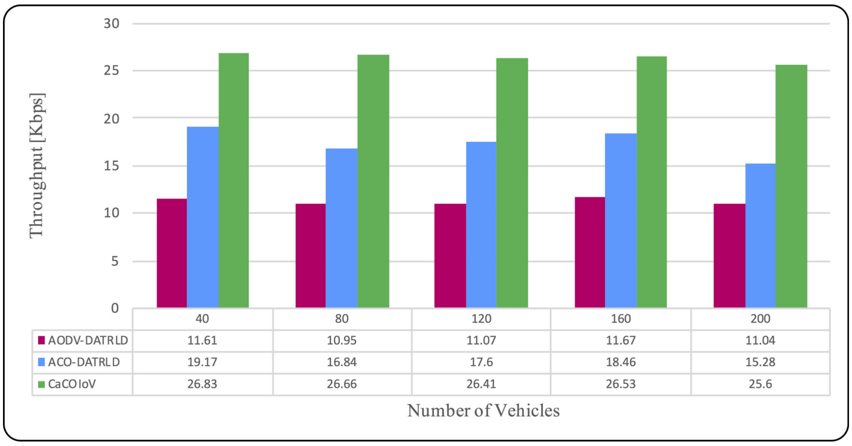

Figure 5. Throughput.

- ***Data Packet Delivery Ratio (DPDR):***

This is a highly essential factor in measuring the routing protocol's performance in any network. Based on the various chosen parameters of the simulation, the protocol's performance is determined. The major parameters consist of the size of packet, number of nodes, range of transmission, and network structure. This metric shows successfully received packet ratio at destination. When the ratio of packet delivery is high, the performance appears to be better. The highest packet delivery ratio in Figure 6 belongs to the proposed algorithm. For all these algorithms we observed a fluctuation of *DPDR* by increasing the number of vehicles from 40 to 160. In the case of increasing vehicles from 160 to 200 on the highway, we noticed an increase of *DPDR*. We can conclude that *DPDR* will decrease by increasing the number of vehicles, especially when comparing the obtained results from with 40 vehicles and 200 vehicles.

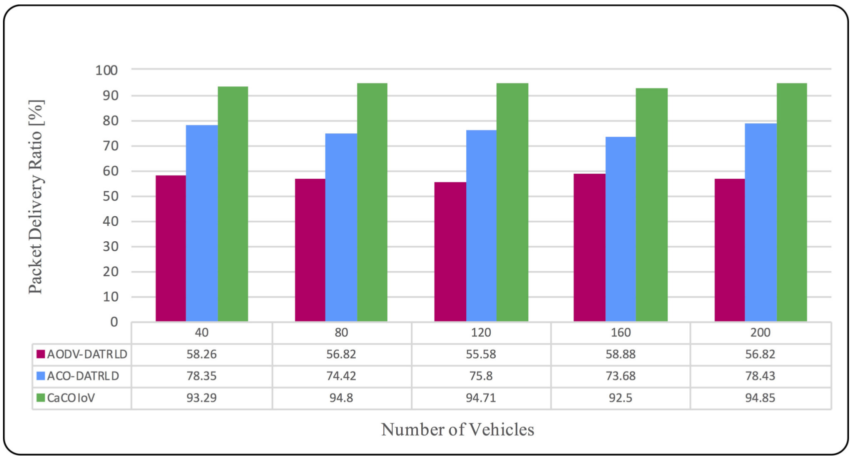

Figure 6. Data Packet Delivery ratio.

- ***Packet Drop Ratio:***

The proportion of packets that never made it to the destination, compared to the originated packets at the source, is the packet loss ratio. The algorithm of the CACOIOV shows that there is much less packet drop ratio during communication in comparison to the others as Figure 7 can clarify. We can clearly see huge differences in packet loss ratio between these protocols in all scenarios. Clearly, the packet drop ratio of CACOIOV is 6 times less than AODV and 3 times less than ACO.

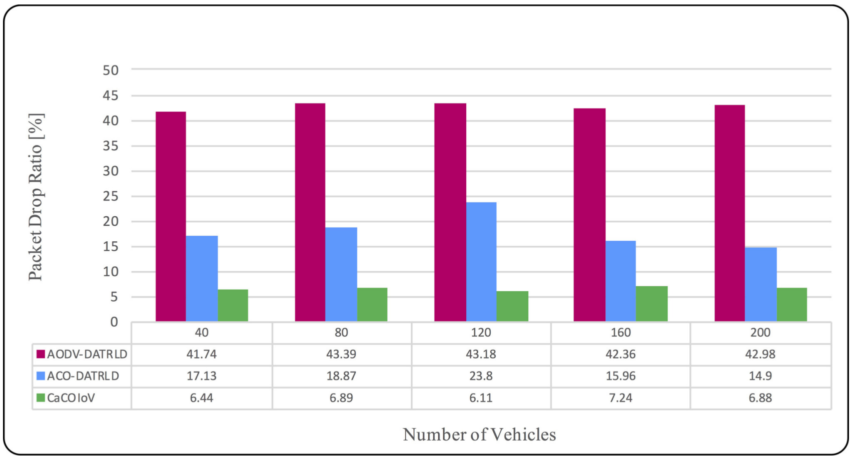

Figure 7. Packet Drop Ratio.

- ***Average End-to-End Delay:***

This can be achieved by computing the mean of end-to-end delay of all messages that are delivered successfully. Hence, this depends partially on the ratio of packet delivery. As there is an increase in the distance among destination and source, the packet drop probability increases. The average end-to-end delay is comprised of possible network delays, such as queuing, buffering, propagation, latency, transfer time, and packet resending at the MAC layer. The CACOIOV algorithm demonstrates significant performance improvement in contrast to other algorithms in terms of average end-to-end delay. it is obvious that by expansion the vehicles number from 40 to 80 in network; this metric increases for CACOIOV and has a negligible increase in cases where there are more than 80 vehicles, which is clarified in Figure 8. Also, by expanding the vehicle number from 40 to 120, delay increases significantly for AODV and we see a sudden delay reduction by increasing vehicles from 120 to 200. ACO has a small delay increase in cases where there are 40 to 160 vehicles in the network. Our interpretation from CACOIOV protocol behavior is expecting negligible increment of delay while the number of vehicles is increasing. We conclude that the impact of our proposed mechanism on the satisfaction of the requirements of real-time applications in IoV increases by minimizing the end-to-end delay.

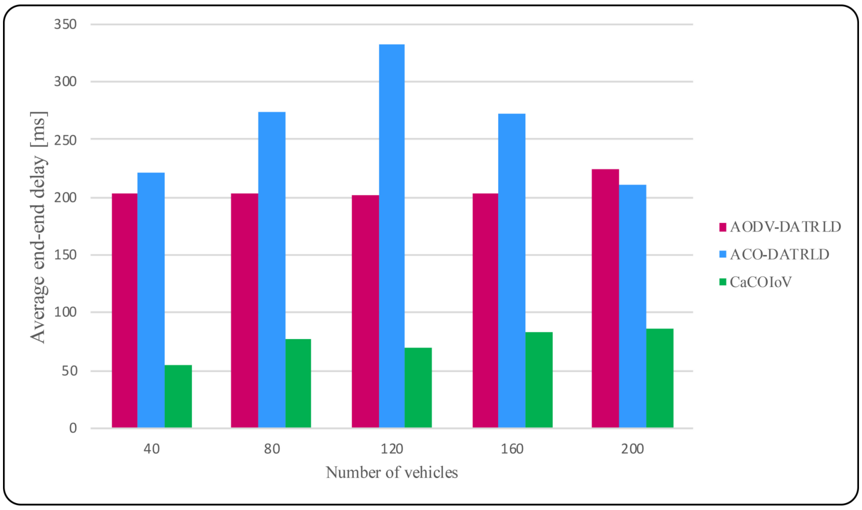

Figure 8. Average end-to-end delay.

- ***Average Number of Cluster:***

A lower number of clusters portrays better communication that the CACOIOV technique achieves on the 4 km^2 grid size. There are two main factors influencing the number of clusters, which are the grid size and the range of transmission. Due to high transmission range, node communication in a larger area of coverage becomes efficient, which reflects minimum clusters in a network. Per node, the range of transmission employed is dynamic for observing their impact on various conditions of networks. The minimum number of clusters mean minimum CHs and more stable and reliable network and clusters. Results of the comparison reveal that when traffic density in the network is high, CACOIOV performs better by forming a minimum number of clusters that shows reliability of our protocol over others. The worst performance belongs to AODV, which has a maximum number of clusters in any traffic density. it is obvious that by increasing the number of vehicles from 40 to 200 in the network, this metric increases, and can be seen in Figure 9. Consequently, increasing the number of vehicles leads to having a greater number of clusters.

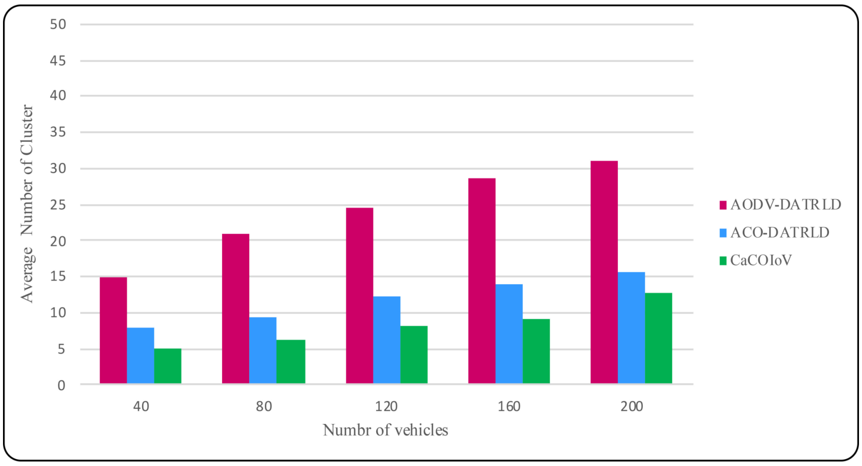

Figure 9. Average Number of Cluster.

5.3. Discussion

According to the obtained results and graphs from the previous section, clearly we can say that our proposed framework/solution (CACOIOV) outperforms the other two algorithms in terms of the mentioned network metrics and is more optimized. The following performance metrics that include packet loss, delay, and formation of cluster numbers have significantly been reduced in the IoV network compared to the ACO and AODV algorithms.

Satiability of cluster and network can be obtained by having a minimum number of clusters. This factor not only has a direct impact on reducing the resource requirements but also decreases the routing cost of whole network. In addition to this, our results also illustrate that throughput and *DPDR* have increased as an outcome of the CACOIOV algorithm. Evidently, CACOIOV has the highest performance compared to others. This achievement is attained in light of three novel and effective ideas. Introducing the selection of first node intelligently in the procedure of CH selection was an efficient step toward the improvement in quality of the ant tour. Proposing the dynamic evaporation idea can be another reason the CACOIOV scheme performs significantly better. This factor balances the convergence process by fastening the convergence speed at the start of route discovery and reaching zero dynamically. Developing this mechanism improved the global search ability remarkably when discovering the best tour/solution that leads to optimized clustering in the network. Finally, the third effective idea for choosing an appropriate vehicle such as a CH is proposing DA-TRLD. This algorithm has a direct impact on the enhancement of cluster stability. All these experimental methods make CACOIOV perform better in all scenarios. Generally, applying DA-TRLD to CACOIOV, ACO, and AODV does not mean that they can have similar performance in all comparison parameters. CACOIOV and ACO have a close result in terms of cluster formation but they differ in other comparison parameters. On the other hand, obtained results of AODV reveal the worst performance compared to others in all cases. Generally, AODV uses the algorithm of route discovery for data transmission among nodes. AODV intention achieves better DPDR and latency prevention. This reactive algorithm propagates a message path failure as Route Error Message (RERR) to all nodes in the network for achieving its goal. As revealed, this algorithm was not successful in providing a better *DPDR* result than the ACO and CACOIOV. In addition, to explain the reason for high end-to-end delay of AODV compared to CACOIOV, we can mention a considerable delay in the process of route discovery of this reactive protocol.

6. Conclusions

Effective communication and management of the network in IoVs are very difficult tasks due to vehicles in fast movement on roads and the effect of speed on data delivery in the formed network. The important need for a method that is systematic and efficient to adjust the parameters of routing protocols and clustering is expressed throughout this research. Also, the IoV and its architecture of communication has been studied. The implementation of the ACO in several ways, and how it is used to optimize solutions, is also addressed. An original methodology, which engages a heuristic multi-objective clustering algorithm based on modified ant colony optimizer (CACOIOV) in two distinct phases is proposed to reach scalable and stable topology in networks of the IoV that are heterogeneous. In the first phase, we proposed a new method for choosing a first node intelligently in the search space and, in the second phase, we introduced a novel way to balance the convergence speed of the ACO by proposing the dynamic evaporation rate method. The presented algorithm makes use of a new proposed DA-TRLD algorithm on the local traffic density basis to maintain connectivity of the IoV network. This method is compared alongside well-known protocols such as ACO and AODV algorithms. The outcome shows satisfactory results regarding packet delivery ratio, delay, cluster number, throughput, and packet drop ratio. Based on developing our novel ideas, we succeeded in accomplishing our study objectives in terms of avoiding local optimum problems and avoiding network dissemination problems. Also, our algorithm clearly demonstrates optimal performance to create efficient and reliable V2I communications that are qualitative, and confirm reliable information delivery to each vehicle. Subsequently, our method provides sustainable transportation in the IoV highway environments for smart cities by developing efficient and reliable protocol for information delivery. Thus, our new framework is a suitable tool for a wide range and large-scale (congested traffic) optimization problem. We hope our proposed protocol insight will help to improve the services provided in the IoV network for the highway environment, and assist drivers in traveling safely.

To verify the CACOIOV performance in realistic environments, it is our intention to implement this framework in traffic simulations with the aid of Open Street Map. Moreover, for future work, several other ACO aspects can be modified to enhance IoV routing. Additionally, urban scenarios can be considered for the deployment of our protocol. Also, the issue of hand-off on the IoV can be explored for the presented protocol.

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