Heuristics-Based Clustering of Internet of Vehicle Based on Effective Approximate QoS Guideline for Message Dissemination

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***Abstract*—Internet of Things and connected world concepts are emerging foreground in all walks of life, and Internet of Vehicles (IoV) is a natural evolution of these concepts for a connected vehicular environment. Clustering is needed in the IoV network for effective management of network resources and to avoid congestion in the network. On the effective cluster base, any efficient routing protocol can be realized for message dissemination. In most of the existing work, clustering based on multiple mobility metrics is the first step, followed by routing over established clusters. This work proposes a clustering solution without the need for frequent clustering or reduced cluster maintenance effort. The proposed solution establishes a virtual QoS guideline path for message dissemination based on graph theory as a first step, and clustering of the network is done to further improve the QoS in the guideline path using a heuristic algorithm. The proposed solution demonstrates notable improvements over existing approaches. Specifically, it achieves an average cluster duration that is at least 6% higher and reduces cluster maintenance overhead by 7%. In terms of Quality of Service (QoS), the solution attains a 3.6% higher packet delivery ratio, along with a 21% reduction in end-to-end delay and a 28% decrease in routing overhead.**

***Keywords*—QoS; clustering; meta heuristics; IoV; PSO; steiner minimal tree**

I. Introduction

The idea behind connected vehicles motivates the revolution of intelligent transportation systems. Communication among connected vehicles can be used to reduce traffic congestion, improve road safety, etc. Vehicles are an important participant in this connected network, with connectivity assisted by direct communication and infrastructure-based communication with roadside units (RSU). Vehicles can use Car-to-Car Communication-Consortium (C2C-CC) and Dedicated Short Range Communication (DSRC), Internet and V2X communication protocols for communication. A major problem in Internet of vehicle networks is scalability and robust routing against topology changes due to vehicular mobility. Clustering is a solution to these problems. Vehicles can be grouped based on similarity of either proximity, trajectory, etc. Message dissemination over a clustered topology has comparatively lower overhead compared to without clustering. Clustering also helps to limit channel contention among cluster members and facilitates fair access. Clustering also assists in spatial reuse of resources like bandwidth. Establishing stable clusters in the presence of higher vehicular mobility is a challenging task. Network topology changes frequently in a vehicular network due to higher vehicular mobility. Under these scenarios, cluster maintenance becomes a huge overhead. Clustering is the basis on which routing algorithms are constructed. When clustering is unstable, maintaining QoS for packet delivery becomes difficult.

Many clustering algorithms have been designed for vehicular networks and are discussed in detail in Section II. These clustering algorithms use various mobility metrics like speed, direction of travel and location of vehicles to organize the vehicles into groups. These algorithms make assumptions about mobility patterns, and when assumptions are challenged, the cluster maintenance effort is huge. Also, the routing protocols built over these clusters have lower QoS when the stability of the cluster is compromised.

In this work, a clustering solution is proposed with reduced cluster maintenance overhead and higher QoS for message dissemination. A virtual QoS guideline path for message dissemination is established as the first step based on graph theory, and clustering is established over the periphery of this guideline path using a soft computing-based heuristic algorithm. The contributions of the suggested work are listed below:

1) A novel virtual QoS guideline path construction based on multi-criteria QoS.

2) An algorithm for clustering based on the virtual QoS guideline path and mobility metrics using heuristics.

The structure of the study is as follows: Section II displays the current clustering algorithms for IoV and critical analysis of their issues. Section III displays the proposed clustering algorithm. The findings of the suggested algorithm are shown in Section IV along with a comparison to previous research. The suggested clustering algorithm's final thoughts and the range of further research are presented in Section V.

II. Related Work

Lakas et al. [1] used link expiration time as the mobility metric for clustering the vehicular network. Once the clustering topology is built using an artificial bee colony algorithm, one can discover paths over clusters with goal of achieving higher QoS. Testing against different scenarios, the approach performed well under the assumption of normal traffic density in highway scenario. When assumption is broken with higher traffic density, QoS deteriorates. Wahab et al. [2] used mobility metrics of velocity and distance to create stable clusters.

Over the clustered topology ant colony algorithm is used for selecting route under the constraint of higher reliability. Direction of movement is not considered while clustering the network. Wang et al. [3] used multiple metrics of link lifetime, node degree, and anticipated transmission count for selecting the head of the cluster. Authors also used an election strategy to select clusters of maximal stability. Over the clustered topology, a weighted routing protocol is proposed where the relay cluster head is selected based on predicted node degree, link life, and transmission time. ON any variation in speed and density, both the stability of the cluster and QoS of routing paths are affected. Khan et al. [4] used the algorithm Moth Flame optimizer for clustering the IoV network. Optimal cluster heads with minimal distance to cluster members are found, so that transmission energy is minimized. The clustering process considered only energy optimization and did not consider other QoS parameters. Ahizoune et al. [5] suggested using a two-stage clustering approach to build durable VANET clusters. In the first stage of setup, clustering is done based on proximity criteria. In the second stage of maintenance, the backup cluster head is selected and role exchange with the primary is done to maintain cluster stability and reliability. The role exchange with the primary is executed to uphold cluster stability and reliability. Cluster stability is quantified by the variance in velocity among vehicles within the cluster. Clustering aims to enhance stability, disregarding QoS parameters. Shankar et al. [6] implemented a hybrid swarm algorithm for clustering in the VANET network, integrating Particle Swarm Optimization (PSO) with the Harmony Search Algorithm (HAS). The fitness function for clustering focuses on minimizing energy consumption. The problem of PSO getting into local minima is solved by using HSA along with PSO. The proposed algorithm improved the lifetime without consideration of QoS parameters. Ali et al. [7] clustered the mobile ad hoc network using particle swarm optimization. The fitness function for PSO was designed based on node degree, transmission power, node’s energy consumption and node’s velocity. The objective of the fitness function was to minimize energy consumption. Fahad et al. [8] used the grey wolf optimization algorithm for clustering the VANET. The optimization criterion for clustering is stability of clusters. Compared to PSO the hunting mechanism of grey wolf was able to converge to better results. Dalbah, et al. [9] came up with JAYACIoV which used an integration of two algorithms k–means and automatic clustering, using 171 testing conditions, providing a 64.82% result. Ayed, et al. [10] addressed the clustering process based on diverse parameters such as the trust value, the safety distance, and the energy factor. Oranj, et al. [11] proposes an algorithm to discover the path based on 2 parameters delay time and reliability. The results are evaluated using NS2 simulator. Shaikh, et al. [12] proposed an algorithm to include security measures within the routing process by efficiently dividing the workload across the alternative paths to reduce the congestion and travel cost. Aadil et al. [13] clustered the VANET network using dragon fly optimization algorithm. The cluster heads were selected based on the speed and direction of the movement. The cluster head transmission range was also adjusted dynamically to increase the cluster coverage. The approach works only for high way scenario. Hadded et al. [14] grouped the VANET using angle-based clustering. The selection of stable clusters is based on the vehicles' angular location and direction. Stability is the only criterion for cluster head selection in this work without consideration for multiple QoS factors. Bersali, M [15] approach CCA-IoV, uses the essential computing and storage capabilities of modern vehicles to operate the clustering process. Gasmi et al. [16] suggested a novel weight-based clustering technique for Internet of Vehicles networks. Density, speed, position, and delay measurements provide the foundation for clustering. QoS in the form of a delay metric was considered in clustering decision. Khan et al. [17] proposed a clustering algorithm for VANETs that is based on connectivity. Links connectivity is used mobility metric for clustering decision. The ideal number of clusters was also determined by the authors using heuristics. In this work, cluster stability—rather than QoS—was the criterion for clustering decisions. Gasmi et al. [18] clustered the IoV network by grouping the nodes moving in the same direction with the same speed. Overall, the clustering fuzzy-based routing algorithm considering QoS was designed. In unstable cluster, providing a guaranteed QoS becomes difficult. Sandeep Yerrathi et al. [19] address the challenges of stability, reliability, and QoS in highly dynamic environments by proposing a novel nature-inspired clustering approach. The African vulture Optimization-Based clustering Algorithm (AVOCA) intelligently forms optimal clusters, reducing network randomness and improving stability across varying grid sizes, node densities and transmission ranges. This study presents a method for cluster head (CH) selection, coordination and maintenance focusing on reducing communication costs. Experiments shows that AVOCA produces up to 45% fewer clusters than existing algorithms like CAMONET, SAMNET, i-WOA and HHO, achieving better load balancing and communication efficiency. Husnain et al. [20] tackle the challenges of dynamic topology and sparse vehicle distribution in VANETs, which complicate stable clustering and routing in Intelligent Transportation systems. To address this, authors proposed an intelligent probability-based bio-inspired Whale Optimization Algorithms (i-WOA) for clustering in VANETs considering factors like communication range, node density, velocity and highway routing. Experimental results across various network scenarios show that i-WOA produces optimal number of cluster heads. Statistical analyses confirm a 75% improvement in clustering optimization, effectively reducing communication costs and routing overhead while extending network lifetime. Jamalzadeh, M et al. [21] address routing challenges on the internet of Vehicle, which is characterized by rapid topology changes and variable node dynamics. They proposed EC-MOPSO, an edge computing assisted, cluster-based routing algorithms that leverages multi-objective particle swarm optimization ((MOPSO), roadside units (RSUs) acts as edge devices to optimize routing by minimizing accumulative delay and hop count while maximizing cluster size. Simulation result demonstrates that EC-MOPSO outperforms existing methods, achieving improvements in distance travelled, latency, packet delivery ratio, and convergence time, making it well-suited for dynamic IoV scenarios. In study done by Husnain et al. [22], a cluster-based routing algorithm inspired by biology is presented in this study for use in Vehicular Ad Hoc Networks (VANETs) in Intelligent Transportation System (ITS) applications. Keeping stable communication routes is difficult because vehicle networks are dynamic and frequently sparse, especially on highways. The Whale Optimization Algorithm (p-WOA), a probability-based approach, is the suggested remedy for enhancing cluster formation in VANETs. Husnain, G et al. [23] The best cluster heads for IoV networks are chosen using a clustering technique based on Harris Hawks Optimization, which takes into account variables like range, node count, grid size, orientation, and velocity. Experimental results demonstrate a 90.6% cluster stability and an 80 percent improvement in cluster optimization, outperforming current techniques in latency, bandwidth usage, and PDR. In the study Abbas et al. [24], HBO-ECHS is a hybrid bio-inspired algorithm that combines BOA and ACO for effective cluster head selection in VANETs. It is proposed in this study. By lowering routing overhead and energy consumption, it improves communication. Comparing NS2 and SUMO simulations to AJ-MOFA and RJ-EDCV, the former demonstrate better PDR, delay, energy efficiency, and routing performance. Salim, A et al. [25] considered the following parameter, like network grid size, average cluster lifespan, and node transmission range for optimal clustering using the sparrow search algorithm (IoVSSA).

III. Proposed Solution

From the survey, most of the clustering algorithms for vehicular network clustered the network based on stability, density and energy. Ensuring the QoS was targeted by the routing algorithm. When assumption made on clustering is broken, the QoS for message dissemination is affected. Also, the overhead for cluster maintenance increases when assumptions are disturbed. The major gaps in existing clustering algorithms are:

- Overhead for cluster maintenance is higher when clustering assumptions are broken.
- Clustering is not based on multi QoS optimization due to which providing higher QoS with routing alone becomes difficult.

This work proposes a heuristics-based clustering algorithm to solve this problem. The algorithm has three stages: i) Construction of QoS guideline path in the network, ii) Clustering with assistance of QoS guideline path and iii) Cluster maintenance.

The network model for proposed solution is given in Fig. 1 shows how the IEEE 802.11p wireless standard allows each vehicle to interact with the RSU and with each other. RSU monitors the vehicular movements in its coverage.

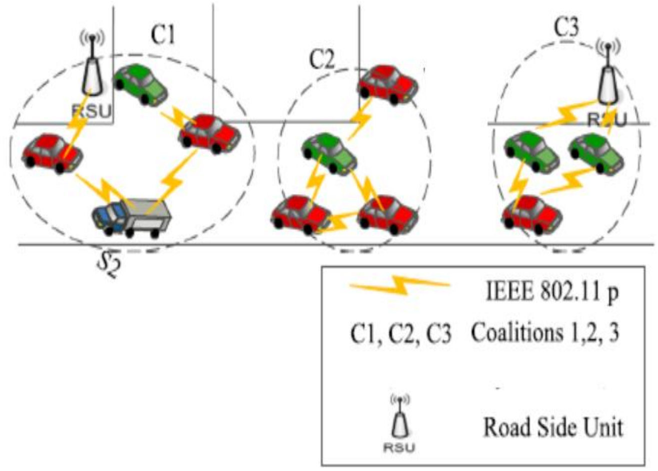

Fig. 1. Network layout.

The vehicular density over period of time (VD_i) in each grid is calculated as:

$$VD_i = \begin{cases} \alpha.T + (1-\alpha)VD_{i-1} \; if \; T \neq 0 \\ (1-\alpha)VD_{i-1}, otherwise \end{cases} \quad (1)$$

where, T is the current density. The grids whose VD_i is above a certain threshold are marked as salient points. A graph is created with all salient points and RSU locations as in Fig. 2. A virtual guideline path is created with minimal hop connectivity to the RSU and salient points. The difficulty in finding the virtual guideline route is solved using the Steiner minimal tree (SMT) problem. It has the feature of introducing intermediate junctions other than RSU to provide more amount of freedom in path construction provided by the Steiner tree.

The Steiner minimal tree is constructed taking P RSU's. The Steiner algorithm must result minimal spanning tree built on S Steiner vertices such that overall length of tree is minimized. Since finding the S points is a NP (non-polynomial) complexity problem, heuristics algorithms are explored to solve it. This work uses Graph iterated 1-steiner (GIIS) [26] to find the Steiner minimal tree.

To apply GIIS, a graph G is created. Each RSU is vertex in the graph G. The delay for packet transmit between RSU is set as edge weight. Delay is intended in terms of probability of distribution over past values as:

$$\text{Delay} = \begin{cases} \sum_{i=0}^{\infty} f_i(a).f_i(b) \;, x = 0 \\ \sum_{i=0}^{\infty} f_i(a).f_{2x+i}(b) + \sum_{i=0}^{\infty} f_i(b).f_{2x+i}(a), x > 0 \end{cases} \quad (2)$$

In the above equation, $f(a)$ is the probability_mass_function in forward_path and $f(b)$ is the probability mass function in backward_path GIIS algorithm finds S optimal Steiner_points, so that cost of Steiner tree found using below equation is minimal for N RSU's.

$$\Delta KMB(N,S) = cost\big(KMB(N)\big) - cost(KMB(N \cup S)) \quad (3)$$

An example of the Steiner tree constructed for RSU is given in Fig. 2. The Steiner points are located at minimal distance to RSU. Steiner points are connected in a minimal tree.

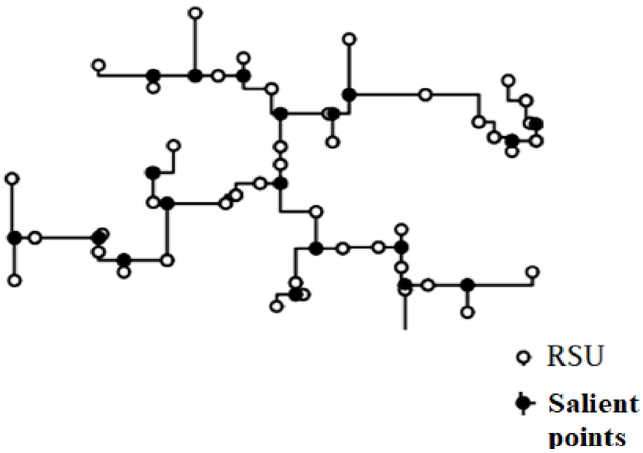

Fig. 2. Virtual guideline path.

The route connecting RSU to Steiner_points and among Steiner_points is the virtual guideline path. The tactical points must be grouped into K groups, where K is the number of data collection points. Grouping of tactical points must be done so that to minimize the delay and maximize the coverage of RSU in the group. Maximizing the coverage and minimizing the delay are two conflicting requirements, and a balance must be achieved between these two conflicting requirements. With increase in the number of strategic points, finding the optimal group is a combinational explosion problem. To solve this problem, nature-inspired heuristics is used in this work. Among multiple heuristics algorithms, particle-swarm-optimization (PSO) is used due to its simplicity.

PSO algorithm is centered on the social actions of swarms. It is a simple, flexible and versatile used to solve many optimization problems. It is centered on the observation that finest solution found by particle in swarm becomes the best solution for entire particles in the swarm. Each particle move randomly in its own velocity and evaluate a fitness function at each position. The position, where maximum value for fitness function is found among all the particles is the global best solution. All other particle update their local position based on the global best solution. This process of updating position and converging to global best solution is repeated in iterations till a maximum fitness function value is obtained or maximum number of repetitions are exceeded.

Each particle (X) updates its position (X_i) at current time based on past location and new velocity $(V_i(t+1))$ as:

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{4}$$

The new velocity is calculated based on past velocity $(V_i(t))$, distance to globally best solution (p_{besti}) and distance to locally best solution (p_{besti}) as:

$$V_i(t+1) = wV_i(t) + c_1 r_1\left(p_{besti}(t) - X_i(t)\right) + c_2 r_2\left(g_{besti}(t) - X_i(t)\right) \tag{5}$$

The important thing to distinguish the best solution is controlled by acceleration coefficient c_1 , c_2 and random number r_1, r_2. The importance to velocity is controlled by intertia weight w.

In this work, each particle represents a group, and it is S bit binary string where each point represents a Steiner point. The value of this position is either 0 or 1, with 0 representing the corresponding Steiner_point not in group and 1 representing the corresponding Steiner_point in group.

The fitness function for particle is calculated as:

$$F = \frac{\sum_{i=1}^{K} |G_i| + 1/SP(G_i)}{K} \tag{6}$$

where, K is the number_of_Steiner_points and $|G_i|$ is the number_of_Steiner_points in the group. SP is the length of minimal route connecting the Steiner_points in the group using Dijkstra's shortest path algorithm. Each particle selects a random binary string as an initial solution. Each particle calculates the fitness function. The particle with the highest value of fitness function is the globally best solution. Based on the globally best solution, the position is the binary string is updated at a certain rate (or velocity). The iteration starts with new solutions and is repeated till there is no change in the binary string or the maximum iterations are reached. The final binary string at the end of the iteration is the solution. The procedure for choosing optimal groups is given below.

Once the Steiner_points are grouped to K groups, the centroid point of each group is selected as the cluster head point.

RSU entrenches the position of the Cluster head points near its neighborhood and sends in the beacon packets. Vehicles check these beacons and if it discovers it position is very near to the cluster head points, it sends a Hello msg broadcast with cluster indicator. Any vehicle observing the Hello msg broadcast joins to this cluster.

Once the vehicle assumed role as cluster head moves, any other vehicle near to the cluster head point will select itself as cluster head and broadcast the Hello msg to request nearby nodes to join its cluster. By this way, the cluster maintenance overhead is lower in our approach. The overall clustering process is given in Fig. 3.

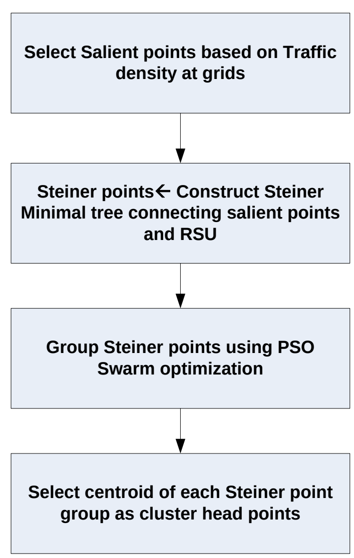

Fig. 3. Clustering process.

IV. Results

The NS-2 simulator is used to evaluate the effectiveness of the proposed solution. SUMO and NS-2 extension code implements the proposed solutions on vehicles traces generated. Simulation runs on the specified configurations, as shown in Table I.

TABLE I. NS-2 SIMULATION CONFIGURATION

Parameters	Values
Propagation_model	Two-way ground
Mobility_model	Krauss
Transmission_range	300m
Transmission_power	20 m W
Simulation_area	4000 m * 4000m
Simulation_time	500s
Message_size	170 bytes

The simulation was conducted against the network layout shown in Fig. 4.

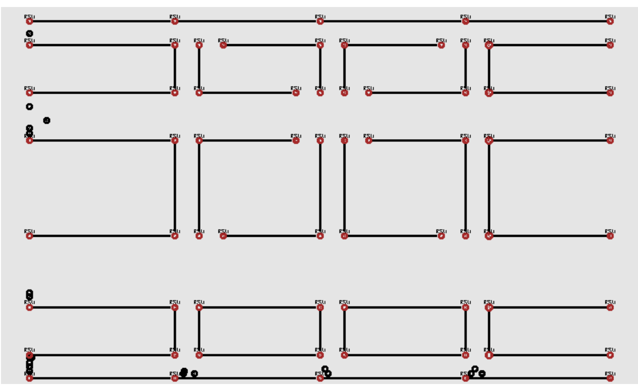

Fig. 4. Network layout.

The proposed solution performance was measured in terms of cluster duration, number-of-clusters, cluster maintenance overhead, packet delivery ratio, delay, and routing overhead. The comparison is done against the proposed solutions and connectivity based clustering proposed by Gasmi et al. [16], connectivity based clustering algorithm proposed by Khan et al. [17] and an unstable connectivity-aware clustering algorithm proposed by Gasmi et al. [18].

The number of clusters was measured for various vehicular speeds and the result is given in Table II.

TABLE II. COMPARISON BASED ON NUMBER OF CLUSTERS

Number of Vehicle	Comparison based on the number of clusters			
	Proposed	*Gasmi.et .al [16]*	*Khan.et.al [17]*	*Gasmi .et.al [18]*
20	7	8	8	9
40	10	11	12	13
60	11	14	13	15
80	12	17	16	18
100	13	19	19	22
Average	**10.6**	**13.8**	**13.6**	**15.4**

In the proposed solutions, the average number-of-clusters is 30% less compared to Gasmi et al. [16], it is 28% less compared to Khan et al. [17] and 45% less compared with Gashmi et al. [18]. The number of clusters is almost stable even at high speeds, as the clusters are created near the stable guideline path instead of vehicular speed and movement mobility metrics used in existing works, as shown in Fig. 5.

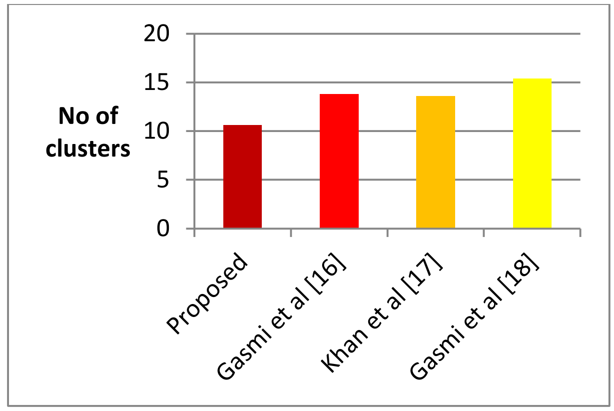

Fig. 5. Average number of clusters.

The average duration of cluster is measured with various vehicular speeds, and Table III shows the result.

TABLE III. COMPARISON OF CLUSTER DURATION

Number of Vehicle	Cluster duration (seconds)			
	Proposed	*Gasmi.et.al, [16]*	*Khan.et.al, [17]*	*Gasmi.et.al, [18]*
20	91	86	87	88
40	86	81	82	82
60	83	77	78	77
80	80	72	74	73
100	79	66	69	68
Average	83.8	76.4	78	77.6

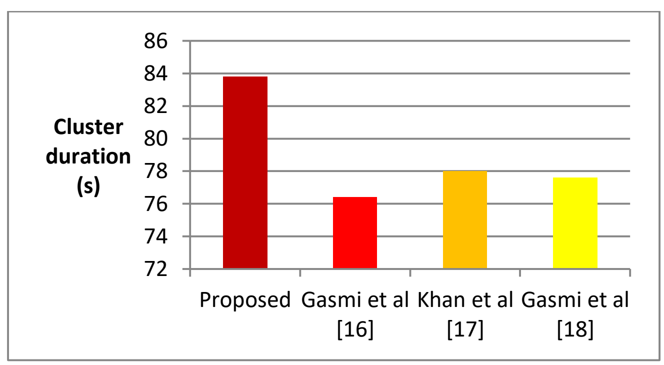

Fig. 6. Average cluster duration.

In the proposed solution the average clustering duration is at least 8% less compared with Gasmi et al. [16], 6% less compared with Khan et al. [17] and 7% less compared with Gasmi et al. [18] as shown in Fig. 6. Clustering duration is higher as the cluster is created based on vehicular movement around the guideline path periphery and optimal cluster selection using PSO based on stability in the proposed solution. The existing works used link stability and node density mobility metrics which varies during higher speeds and thus their clustering duration is lower. They compensate for it by increasing the number of clusters.

The packet delivery ratio was measured for various vehicular speeds and Table IV shows the above results.

TABLE IV. COMPARISON OF PACKET DELIVERY RATIO

Number of Vehicle	Comparison Of Packet Delivery Ratio			
	Proposed	*Gasmi et al. [16]*	*Khan et al. [17]*	*Gasmi et al. [18]*
20	93	90	91	90
40	91	89	89	88
60	90	86	87	87
80	89	85	84	85
100	88	83	82	83
Average	90.2	86.6	86.6	86.6

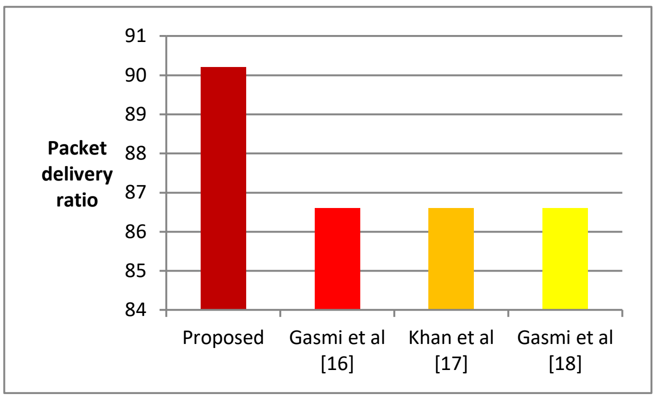

Fig. 7. The proposed and existing packet delivery ratio.

In the proposed solution, the packet delivery ratio is 3.6% high compared with existing works, as shown in the Fig. 7. Due to creation of more stable clusters and ability to search the hop cluster for data forwarding along the virtual guideline path increases the packet delivery ratio. The presence of virtual guideline path was the differentiator in the proposed solution compared to existing works.

By varying the speed, the average packet delay is measured, and the result is shown in Table V.

TABLE V. COMPARISON OF DELAY

Number of Vehicle	Delay (milli seconds)			
	Proposed	*Gasmi et al. [16]*	*Khan et al. [17]*	*Gasmi et al. [18]*
20	17	18	19	19
40	21	24	24	25
60	24	28	27	28
80	25	33	32	34
100	25	34	34	37
Average	22.4	27.4	27.2	28.6

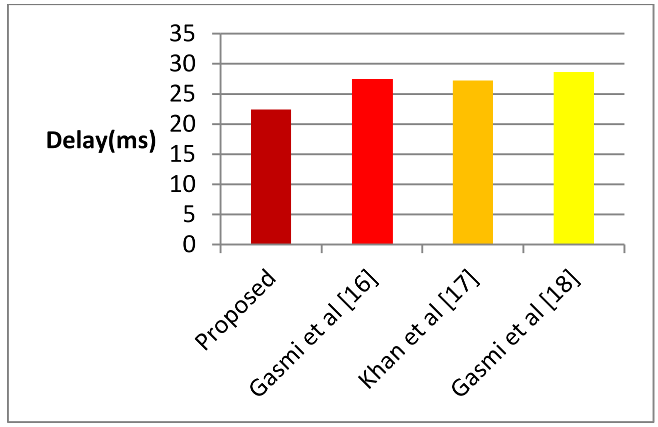

Fig. 8. Delay.

The average packet delay in the suggested solution is 22% low compared with Gasmi et al. [16], 21% lower compared with Khan et al. [17] and 27% lower compared with Gasmi et al.[18] as shown in the Fig. 8. The packet delay has been reduced in proposed solution due to clusters around the periphery of the virtual guideline path which is constructed with delay as one of the optimization criteria. The cluster maintenance overhead in terms of volume of packets exchanged is measured for various speeds and result shown in the Table VI.

TABLE VI. COMPARISON OF CLUSTER MAINTENANCE OVERHEAD

Number of Vehicle	Cluster maintenance Overhead (KB)			
	Proposed	*Gasmi et al [16]*	*Khan et al [17]*	*Gasmi et al [18]*
20	31	33	32	33
40	37	39	37	38
60	43	46	45	44
80	45	49	51	49
100	48	54	54	55
Average	40.8	44.2	43.8	43.8

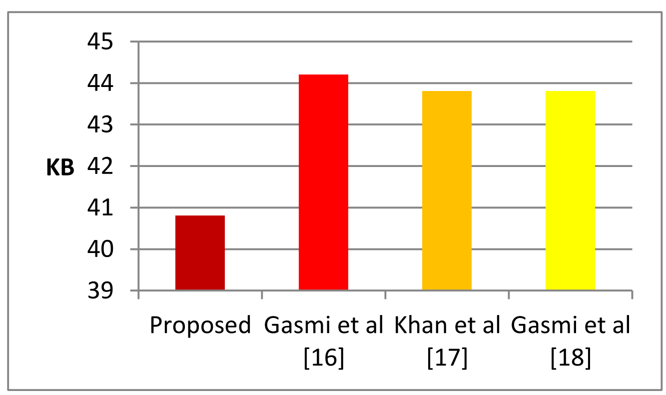

Fig. 9. Cluster maintenance overhead.

In proposed solution, the clustering maintenance overhead is 8% low compared with Gasmi et al. [16], 7% low compared with Khan et al. [17] and 7% low compared with Gasmi et al. [18], as shown in Fig. 9. The cluster maintenance overhead is low due to reduction of search space of new cluster in proposed solution. The clusters are only selected along the periphery of virtual guideline path instead of many locations in the networks in proposed solution. The routing overhead in terms of retransmissions or route construction effort is measured for various speeds and result shown in Table VII.

TABLE VII. COMPARISON OF ROUTING OVERHEAD

Number of Vehicle	Routing Overhead (KB)			
	Proposed	*Gasmi.et.al [16]*	*Khan.et.al [17]*	*Gasmi.et.al [18]*
20	11	12	13	14
40	13	15	16	17
60	15	19	21	22
80	17	24	25	27
100	19	26	27	29
Average	15	19.2	20.4	21.8

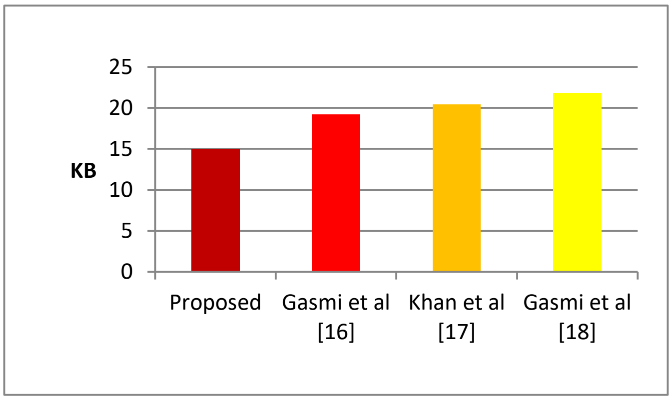

Fig. 10. Routing overhead.

In proposed solution, the routing overhead is 28% low compared with Gasmi et al. [16], 36% low compared with Khan et al. [17] and 45% low compared to Gasmi et al. [18], as shown in Fig. 10. Due to the use of RSU assistance in routing and routing along virtual guideline path, the routing overhead is reduced.

V. CONCLUSION

A heuristics-based clustering algorithm is proposed in this work for IOV network. A virtual guideline path is first established based on multi QoS and Clusters are established around the periphery of the virtual guideline path. The proposed solution can establish stable clusters with reduced cluster maintenance overhead. The average cluster duration is at least 6% higher and cluster maintenance overhead is 7% lower compared to exiting works. In terms of QoS, the proposed solution has 3.6% high packet delivery ratio and 21% low, 28% low routing overhead compared to existing works.

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