Improving QoS in Internet of Vehicles Integrating Swarm Intelligence Guided Topology Adaptive Routing and Service Differentiated Flow Control

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***Abstract*—Internet of Vehicles (IoV) is an evolution of vehicular adhoc network with concepts of internet of things (IOT). Each vehicle in IOV is an intelligent object with various capabilities like sensors, computation, storage, control etc. Vehicles can connect to any other entity in the network using various services like DSRC, C2C-CC etc. Ensuring QoS for vehicle to everything (V2X) communication is a major challenge in IoV. This work applies an integration of hybrid metaheuristics guided routing and service differentiated flow control to ensure QoS in Internet of Vehicles. Clustering based network topology is adopted with clustering based on hybrid metaheuristics integrating particle swarm optimization with firefly algorithm. Over the established clusters routing decision is done using swarm intelligence. Packet flows in the network are service differentiated and flow control is done at cluster heads to reduce the congestion in the network. High congestion in routes is mitigated with back up path satisfying the QoS constraints. Due to optimization in clustering, routing and data forwarding process, the proposed solution is able to achieve higher QoS. Through simulation analysis, the proposed solution is able to achieve 2% higher packet delivery ratio and 9.67% lower end to end packet latency compared to existing works.**

Keywords*—*Particle swarm optimization (PSO); QoS; bio inspired technique

I. INTRODUCTION

Internet of Vehicles is seen as a most promising solution to address the challenges of modern transportation like improving road safety, mitigating traffic congestion, reduce fuel consumption etc[1]. Each vehicle is an intelligent object with sensing, computing, storing, control and communication facilities. Vehicles can connect to any entity within vehicular adhoc network (VANET) like Road Side Units (RSU), other vehicles and entities outside network like application servers, cloud etc. The connectivity is enabled using various mechanisms like dedicated short range communication (DSRC), car to car communication consortium (C2C-CC) etc. IoV is different from traditional IoT networks as it can generate information volume thousand times more than traditional IoT networks. IoV need to support messages of different categories like emergency messages, real time cooperative control messages, infotainment message etc with different delay and reliability constraints. Supporting wide variety of IoV applications with guaranteed quality of service (QoS) is a challenge in IoV networks. QoS requirements are in terms of packet delivery ratio, delay and jitter. Due to vehicle movement, network topology is dynamic and connectivity between vehicles is on constant change. This affects the stability of the routes and in turn affects all the QoS parameters. Providing guaranteed QoS in highly dynamic IoV network is a very challenging multi constraint optimization problem [2]. The optimal solution to this problem can be found through hybrid metaheuristics.

In this work, an integrated solution combining hybrid metaheuristics for topology adaptive routing and service differentiated flow control is proposed to provide guaranteed QoS in IoV networks. The network is partitioned to clusters with efficient cluster head selection using hybrid metaheuristics based multi criteria optimization. Clustering is adaptive for a hybrid IoV with or without RSU availability. A QoS guaranteed routing using Ant colony optimization is proposed on the clustered topology. In addition it, packet flows in the network is differentiated and flow control is done at cluster heads to reduce the congestion and facilitate differential QoS for different services. In short, the proposed work is able to provide differential QoS guarantee for different services in IoV through three factors of topology control, topology adaptive routing and service differentiated flow control. Compared to earlier works addressing any one particular area of topology, routing or data forwarding optimization the proposed solution integrates optimization in all three areas of topology, routing and data forwarding. This integration has provided added advantage in achieving higher QoS in proposed solution.

The paper is organized as follows. Section II presents the existing works in VANET for ensuring higher QoS and their shortcomings. Section III presents the research gap. Section IV presents the proposed solution integrating clustering, routing and data forwarding optimizations to ensure higher QoS. Section V presents the novelties in the proposed solution. Section VI presents the results of the proposed solution and its comparison to existing works. Section VII presents the conclusion and scope of future work.

II. RELATED WORK

Authors in [3] proposed a QoS routing protocol for VANET. The protocol is designed specifically for high wayscenario. The network is clustered with cluster head selected based on the link expiration time of the neighbors. Artificial Bee Colony (ABC) algorithm is used to find the optimal path with higher QoS. This work enforces QoS requirements both during clustering and routing. The performance of solution was tested against different traffic scenarios and the work was found to perform well for highway scenario where traffic density is normal. The performance degrades for higher urban traffic density. Authors in [4] proposed a QoS based clustering algorithm for mobile adhoc networks. The algorithm tries to create stable clusters and maintain stability during communications and link failure at the same time considers QoS requirements. Mobility metrics like velocity and distance are added to QoS functions to select stable clusters. The relay nodes for routing are selected using ant colony algorithm with requirement of satisfying mobility and stability constraints. A cheating prevention mechanism is also proposed in this work for fair and reliable relay selection. Direction of movement, load processed by MPR and packet flow categories are not considered in this work. A passive clustering aided routing protocol is proposed in [5] to improve the routing performance for one way multi-lane highway scenario. A multi metric distributed election strategy using metrics such as node degree, expected transmission count, and link lifetime is proposed for cluster head selection. The election strategy tries to maximize the stability of cluster structure. A weighted routing protocol based on metrics of expected transmission time, link life time and node degree is used for selecting the best relay cluster head. The work could not accommodate dynamic variation in speed and density. Authors in [6] proposed a QoS multicast routing protocol for VANET based on bee communication principle. The proposed protocol is able to find and maintain robust route between the source and multicast group members. The path is selected to maximize the average bandwidth and packet delivery ratio at same time minimizing the end to end delay and normalized overhead load. Failure of link cause due to vehicle dynamics is not considered for multicast tree reorganization in this work. A situation aware multi constrained routing protocol is proposed in [7] for VANET combining situational awareness and ant colony algorithm. From among multiple feasible routes between source and target vehicle, a best route satisfying multiple QoS constraints and reliability metrics is found. The reliability risks in the best route selected is mitigated using situation awareness and ant colony optimization by proactively predicting link failure and replacing them with backup links. The work predicts only movement based failures, but could have been extended for congestion based failures. Authors in [8] proposed a clustering algorithm for IoV network with nature inspired Moth flame optimizer. The cluster heads are selected in such a way that average of distance between cluster members to cluster head is minimal in the network. By minimizing the distance, the transmission energy is also reduced in the network. Clustering did not accommodate any QoS requirements in this work. A new stability based clustering algorithm is proposed for VANET is [9]. The algorithm has two stages: setup and maintenance. In setup stage, close proximity nodes are organized to clusters with selection of cluster head. In maintenance stage, a backup cluster head is selected and it becomes primary to maintain stability and reliability of cluster. The stability of cluster is measured in terms of velocity differences between the vehicles in the cluster and this difference is important criteria for clustering in this work. QoS requirements are not considered as criteria for clustering in this work. Authors in [10] proposed a hybrid of harmony search algorithm (HSA) and PSO algorithm for cluster head selection in sensor networks. The cluster heads are selected to minimize the energy consumption in the network. With high search efficiency of HSA and dynamic capability of PSO, efficient clustering of network is done resulting in increased life time of the network. Authors in [11] used multi objective particle swarm optimization to optimize the number of clusters in adhoc network.Degree of nodes, transmission power, energy consumption of nodes and velocity of nodes and are the parameters considered for optimization. The goal of cluster head selection is to reduce the overall energy consumption in the network. Authors in [12] proposed a clustering algorithm for VANET using grey wolf optimization. Social behavior and hunting mechanism of grey wolfs are replicated to create efficient clusters. Stability of clusters is the optimization criteria for the fitness function in grey wolf optimization algorithm. Authors in [13] proposed two bio inspired evolutionary algorithms for clustering in VANET – comprehensive learning PSO and Multi objective PSO. Maximizing the number of cluster members without affecting the stability due to velocity of the vehicles is the optimization criteria used in both the evolutionary algorithms. Authors in [14] proposed a clustering algorithm using ant colony optimization for VANET. The variables considered for clustering are distance of neighboring nodes from cluster head, speed of vehicles, direction of cluster head and cluster nodes within a cluster. The algorithm tries to find the minimal number of clusters so that packet routing cost is minimized. Dragon fly optimization algorithm is used for clustering VANET in [15]. The approach also adapted the transmission rage dynamically based on the traffic density and mobility pattern. Dragon fly fitness function for cluster selection is based on speed, velocity and direction of the vehicles. A routing algorithm integrating ant colony optimization with Dynamic MANET (DYMO) on demand protocol is proposed for VANET in [16]. The path selection is based on two parameters of hop distance and path reliability. Path reliability is measured in terms of expected number of transmissions. Authors in [17] proposed a efficient clustering for flying adhoc networks. A variant of K-means density clustering algorithm is used for selection of cluster heads. Transmission power of nodes is adjusted based on their operational requirements. The approach works only for low mobility of nodes. Authors in [18] proposed a novel path planning algorithm for reliable and efficient routing in VANET. Congestion is manager by distributing load over alternate paths and splitting the larger packets to small packets. Routing is based on multiple QoS constraints of packet delivery ratio and energy. Authors in [19] proposed a novel, secure and reliable multi constrained QoS aware routing algorithm for VANETs. Ant colony optimization is used to compute feasible routes ensuring differential reliability for different traffic types. Authors in [20] proposed a novel moving zone based routing protocol. The moving zone is formed by clustering the vehicles with similar movement patterns and trajectories. A coordinator node is selected for each moving zone to assist in message dissemination. Authors in [21] used ant colony optimization for selection of routing paths with higher QoS in VANET. The factors considered for QoS improvement in this work were packet delivery ratio, delay and link connectivity. Routing to improve QoS based on vehicle orientation is proposed in [22]. The salient part of this work is that it translated multi constraint QoS objectives to single constraint objectives using a cosine similarity scalarization model. Authors in [23] proposed an angle based clustering algorithm for VANET. The most stable vehicles that can act as cluster head are selected based on the angular position and direction of the vehicles. Each vehicle builds its neighborhood information using an angular technique. Clusters are created based on this neighborhood information. Authors in [24] used the concept of location aided routing to propose a reactive routing protocol for VANET. The protocol used multi objective particle swarm optimization for searching the route. Authors in [25] surveyed different QoS routing protocols in VANET. The study observed QoS cannot be guaranteed in VANET only with routing and it needs much more mechanisms like flow control, class differentiation etc. The solution proposed by us is in this direction of integrating flow control and class differentiation along with routing and topology control for guaranteed QoS in VANET.

III. Research Gap

- Following are some of important research gaps identified from the survey
- Most of the existing solutions consider ensuring QoS in IoV as topology control and routing problem without consideration of different services and their QoS needs. Better QoS management strategy must also consider service differentiation and flow control along with topology and routing management.
- Most of existing multi objective optimization based clustering works use limited parameters like velocity, direction etc, without consideration for their resource capability. Multi objective optimization based clustering methods must also include resource metrics affecting QoS, so that the QoS can be improved in the network.
- In this work, we address the above two open issues and design a swarm intelligence guided topology and routing management with multi objective QoS guarantee and integrating it with service differentiated flow control for better QoS management in IoV.

IV. Proposed Solution

The proposed solution for improving QoS in IoV has following important functionalities

A. *Multi Objective QoS Constrained Clustering*

Multi objective QoS constrained clustering is implemented using particle swarm optimization (PSO). Each particle is the array of length N with each element in the array is the ID of the cluster head node. Each particle covers whole of the network and particle does not have any duplicate ID. The multi objective particle swarm optimization algorithm proposed in [11] is adapted. While the approach [11] is designed with goal of clustering for energy optimization, in this work, clustering is done for multi objective QoS optimization. A new multi constraint QoS objective function is introduced. The function considers following parameters

- Average Stability of cluster (S)
- Average effective hop count between clusters (h_c)
- Average Degree difference (D_d)
- Average uncovered vehicles on speed/direction variations. (U_C)

In [9], the objective values are measured for each cluster head in the particle and they are then summed up to provide the total objective value for the particle. Deviating from it, this work models selects the cluster heads as a multi objective optimization problem using hybrid metaheuristics. Compared to using single optimization algorithm, use of hybrid metaheuristics solves the problem of local minima. Combining algorithms with contrasting features of exploration and exploitation results is optimal solution avoiding the local minima. In this work Particle swarm optimization (PSO) with exploration capability is combined with firefly algorithm with exploitation capability to select the optimal cluster heads.

PSO is a swarm intelligence algorithm (Kennedy et al 1995) simulating the social behavior of swarm of organisms. This method is popular for solving optimization problems due it its simplicity, flexibility and versatility. Organisms move randomly with different velocities and use these velocities to update their individual position. Each candidate solution is a ‘particle’. Each particle tries to attain its best velocity based on its own local best (p_{best}) value and its neighbor’s global best (g_{best}). Each particle’s next position depends on the current position, current velocity, distance from current position to p_{best}, distance from current position to g_{best}. The movement of particle in its search space depends on its velocity. For a particle X, it current position X_i and current velocity V_i is updated as

$$X_i(t+1) = X_i(t) + V_i(t+1) \qquad (1)$$

$$V_i(t+1) = wV_i(t) + c_1 r_1\big(p_{besti}(t) - X_i(t)\big) + c_2 r_2\big(g_{besti}(t) - X_i(t)\big) \qquad (2)$$

In the above equations, t is the iterative value. c_1 and c_2 are acceleration coefficients, .r_1 and r_2 are random numbers, w is the inertia weight. The iteration is repeated till termination condition is met.

Firefly is swarm intelligence algorithm (Yang et al 2008) based on the behavior of fireflies in naturally occurring environment. Fireflies exhibit unique light flashes for various purposes like mating, warning about potential danger etc. Fireflies operation is guided by two parameters: light intensity and level of attractiveness. Light intensity (I) is inversely proportional to the distance between the emitting and observing firefly (r). It is given as

$$I = \frac{1}{r^2} \qquad (3)$$

Level of attractiveness is proportional to the light intensity. It is calculated as

$$\beta(r) = \beta_0 e^{-\gamma r^2} \qquad (4)$$

β_0 is the attractiveness at r=0 and γ is the light absorption coefficient. Euclidean distance formula is used for calculating r.

The movement of firefly (FX_i) governed by attraction from another firefly (FX_j) is calculated as

$$FX_i = FX_i + \beta_0 e^{-\gamma r^2}(FX_j - FX_i) + \alpha\epsilon_i \quad (5)$$

In the above equation α is the randomization parameter and ϵ_i is a random number.

The hybrid metaheuristics algorithm for clustering first invokes firefly algorithm to select the cluster heads with random cluster heads as input. PSO algorithm is then started with the cluster heads selected by firefly as input and the output of the PSO is the optimal cluster heads.

The fitness function for selection of optimal cluster heads is framed as

$$F_f = w_1 S + w_2 h_c + w_3 \frac{1}{D_d} + w_4 \frac{1}{U_C} \quad (6)$$

Firefly algorithm is started with K fireflies each firefly has N bit string with M (number of desired cluster head) out it is marked as 1 and rest marked as 0. Value of 1 represents, the corresponding node is cluster head. The initial N bit string is formed randomly. Firefly algorithm is run with fitness function defined in Eq. (6) on each iteration and the firefly with maximum value for F_f is selected as best and movement of other firefly is done based on best firefly. Once the maximum iteration is reached or error has reached minimum value firefly algorithm is stopped and N bit string of the best firefly is taken as the seed. From this seed, K particles are initialized with N bit string by toggling P random positions. The PSO algorithm is then started with this solution formed from firefly. At each iteration, the fitness function defined in Eq. (6) is calculated and the particle is maximum value for F_f is selected as globally best solution. Once the maximum iteration is reached or error has reached minimum value PSO algorithm is stopped and N bit string of the globally best particle is taken. The positions where 1 is marked in N bit string are taken and the corresponding nodes are made as cluster heads.

B. QoS based Routing

The proposed QoS based routing uses both two different routing modes: vehicle to cluster head and cluster head to cluster head. Vehicle to cluster head is through geographic routing. Cluster head to cluster head routing is using ant colony optimization algorithm.

The source vehicle which needs to send packet to destination vehicle sends routing request message to the source cluster head. The routing request message also carries the service identifier. Source cluster head initiates a group of forward ant in search of the destination vehicle cluster head. The service identifier is carried in the forward ant. When forward ant reaches any cluster head i, it records the cluster head ID and transmission delay, it makes a decision to choose the next cluster head based on the global pheromone (gp) and local pheromone (lp) stored at cluster head i. The probability of selecting the next cluster head j is given as

$$p_{ij} = \frac{gp_{ij}^{\alpha} lp_{ij}^{\beta}}{\sum_{m=1}^{K} gp_{im}^{\alpha} lp_{im}^{\beta}} \quad (7)$$

Where K is the number of next hop cluster heads to i. α, β are the weight values. Local pheromone (lp) and global pheromone(gp) is calculated in terms of QoS requirements as

$$lp_{ij} = w_1 C_p(e_{ij}) + w_2 pdr_p(e_{ij}) + w_3 d_p(e_{ij}) + w_4 j_p(e_{ij}) + w_5 L_p(e_{ij}) \quad (8)$$

Where w_x is the weight associated with each factor such a way that

$$\sum_{x=1}^{5} w_x = 1 \quad (9)$$

e_{ij} is the link between cluster head i and j. C_p is the connection probability ,pdr_p is the predicted packet delivery ratio,d_p is the predicted delay, j_p is the predicted jitter and L_p is the predicted link expiration time.For two cluster heads u and v positioned at (x_u, y_u) and (x_v, y_v) , moving with velocity v_u and v_v in direction of θ_u and θ_v , the link expiration time is calculated as

$$L(u,v) = \frac{\sqrt{d^2(a^2+c^2)-(ad-bc)^2-(ab+cd)}}{a^2+c^2} \quad (10)$$

Where

$$a = v_u cos\theta_u - v_v cos\theta_v$$

$$b = x_u - x_v$$

$$c = v_u sin\theta_u - v_v sin\theta_v$$

$$d = y_u - y_v$$

In each link, the past values of delivery ratio, connectivity probability, delay and jitter are collected. Based on the previous history, prediction over new interval is done applying exponential moving average as

$$v(t+1) = \alpha * x + (1-\alpha)v(t) \quad (11)$$

Where x is the current observed value and $v(t+1)$ is the predicted value. α is a constant.

When forward ant arrives at destination cluster head, it checks the delay value in the forward ant against the delay threshold set for the service. If the delay in the forward ant is less the delay threshold, the path passed by the ant is selected as a probable candidate route. The forward ants which arrive through candidate route are converted to backward ant. The backward ant traverses back to the source cluster head. As it traverses, its updates the global pheromone value as

$$gp_{ij} = (1-\delta)gp_{ij} + \delta * best\ local\ phenome\ value\ over\ the\ path \quad (12)$$

Once all backward ants arrive at source cluster head, for each backward ant, a QoS fitness score fs is calculated for the route provided by the backward ant. The route having the highest value forfs is the path used for routing between source and destination cluster head. QoS fitness score fs is calculated as

$$fs(P_x) = w_1 C_p(P_x) + w_2 pdr_p(P_x) + w_3 d_p(P_x) + w_4 j_p(P_x) + w_5 L_p(P_x) \quad (13)$$

Where P_x is the path traversed by the backward ant.

The backward ant calculates the C_p of entire path as minimum value of connection probability of all links in the path. It calculates the pdr_p of entire path as minimum value of packet deliver ratio of all links in the path. It calculates the d_p of entire path as maximum value of delay of all the links in the path. It calculates the j_p of entire path as maximum value of jitter of all the links in the path. It calculates the L_p of entire path as minimum value of link expiration time of all links in the path.

C. Service Differentiation and Flow Control

The flows or sessions in the network are categorized based on the services to different priorities. At each of the cluster head, a differential flow control is done. Cluster head maintains multiple queues, each corresponding to a priority for queuing the incoming packets. Different from allocating processing slots based on priority alone, in this work, we use estimated traffic demand in each priorities, priority of the packet and estimated congestion on immediate forwarding links as the three parameters for allocating processing slots to the queues. The processing slots are grouped into time frames. The traffic demand for each priority queue is estimated as

$$DQ = \min(MA_i + D_i, T \times \Delta) \tag{14}$$

The exponential moving average of incoming traffic to queue MA is calculated with D as total packets in queue and physical transmission rate as T as

$$MA_i = \begin{cases} \alpha . T + (1-\alpha)MA_{i-1} \; if \; T \neq 0 \\ (1-\alpha)MA_{i-1}, otherwise \end{cases} \tag{15}$$

From the estimated traffic demand the slots ns for queue $x$is allocated out of N total slots as given below:

$$ns_x = \frac{FD_x}{\sum_{x=1}^{n} FD_x} * \frac{P_x}{\sum_{x=1}^{n} P_x} * N \tag{16}$$

Where P is the priority of queue. The total slots N is not fixed and it should be adapted to congestion on immediate forwarding links. We model congestion in terms of predicted round trip time(RTT). RTT prediction is done as a probability mass function of past delay distribution. It is calculated as:

$$RTT = \begin{cases} \sum_{i=0}^{\infty} f_i(a). f_i(b) \;, x = 0 \\ \sum_{i=0}^{\infty} f_i(a). f_{2x+i}(b) + \sum_{i=0}^{\infty} f_i(b). f_{2x+i}(a), x > 0 \end{cases} \tag{17}$$

The forward direction for packet travel is denoted as a. The backward direction for packet travel is denoted as b. The probability mass function of delay in direction v is denoted as f(v).

From the predicted RTT, the value of N is calculated as:

$$N = \frac{k}{RTT} \tag{18}$$

Where, k is the total number of messages that can be forwarded when RTT is at a best lower bound value. This value is configured by network administrator.

V. Novelty in Proposed Solution

Following are the novelties in the proposed solution

- Ensuring QoS in IoV is solved through an integrated solution combining QoS based topology control, QoS based routing and service differentiated flow control.
- Clustering using swarm intelligence considers multiple QoS metrics in addition to usual parameters of velocity, direction, etc.
- Multi class multi QoS optimization based ant colony optimization is done to find effective routes for different service flows.
- Adaptive service differentiated flow control based on network congestion feedback is proposed.

VI. Results

NS2 simulator is used for measuring the effectiveness of the proposed solution. The vehicle traces are generated using SUMO and NS2 extension code implements the proposed solution on these traces.

The simulation was conducted against configuration parameters in Table I.

TABLE I. SIMULATION CONFIGURATION

Sl no.	Simulation Configuration	
	Parameter	***Value***
1	Road length	***4Km***
2	Road length	***4Km***
3	Road topology	***Highway***
4	Number of lanes	***4***
5	Vehicle density	***25 to 200***
	Vehicle speed	***30 m/s***
7	Transmission range	250 m
8	***MAC protocol***	***IEEE 802.11 p***
9	***Data packet size***	***1000 bytes***
10	***Data rate***	***5 packet/second***
11	***Simulation time***	***1000 seconds***

Four different traffic types are used for simulation. The traffic types and their priorities are given in Table II.

TABLE II. TRAFFIC CLASSES

Sl no.	Simulation Configuration	
	Traffic class	***Priority***
1	Bulk transfer	2
2	Audio	3
3	Video	3
4	General applications	5

The performance of the proposed solution is compared against CBQoS-Vanet [3] and SAMQ [7] in terms of following metrics:

- Packet delivery ratio
- Packet dropped ratio
- Normalized overhead load
- Average end to delay
- Throughput

Varying the number of vehicles, packet delivery ratio is measured and the results are given in Fig. 1.

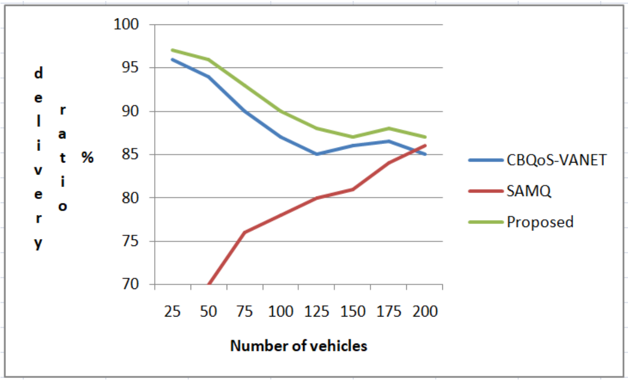

Fig. 1. Packet delivery ratio.

From the Fig. 1, it can be seen that in both CBQoS-VANET and Proposed, as the vehicle density increases, the delivery ratio drops. But the delivery ratio in Proposed is much higher compared to SAMQ and CBQoS-VANET. The increase in delivery ratio in the proposed when compared to CBQoS-VANET is due to implementation of flow control in the proposed. On an average packet delivery in the proposed solution is 2.07 % more compared to CBQoS-VANET and 12.88% more compared to SAMQ.

The results of packet dropped ratio for different vehicle density is given in Fig. 2.

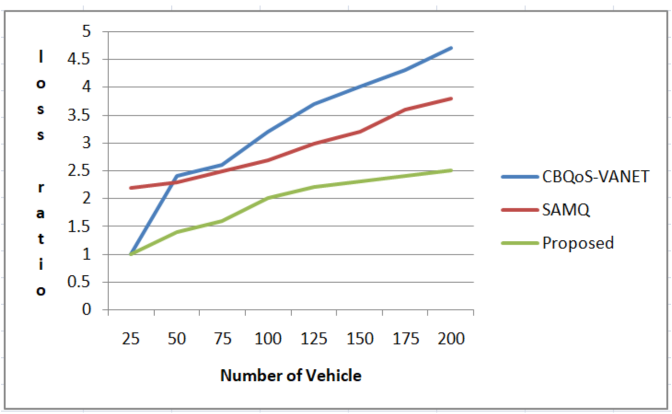

Fig. 2. Loss ratio.

From the Fig. 2, it can be seen that although the loss rate is within 2 to 6% in all the three protocols, best performance is achieved in proposed with average loss rate 70% lower compared to CBQoS-VANET and 53.15% lower compared to SAMQ. Congestion is controlled based on RTT feedback in the proposed solution. Due to this, the loss rate is lower in the proposed solution.

Varying the vehicle density, normalized overhead is measured and the result is given in Fig. 3.

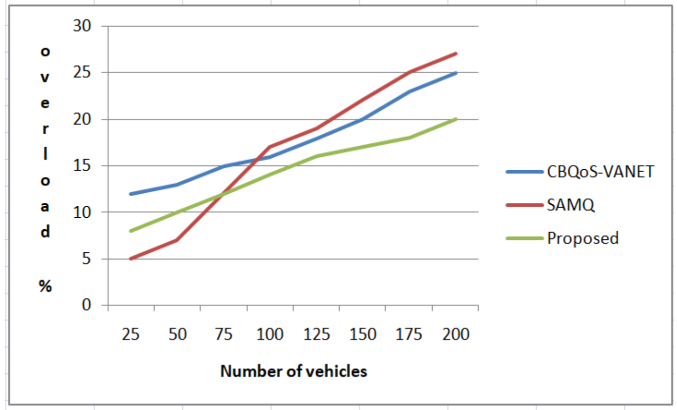

Fig. 3. Network overhead.

From the Fig. 3, the normalized overload in the proposed solution is on average is 16.52% lower compared to SAMQ and 23.47% lower compared to CBQoS-VANET. The overhead increases with higher vehicle density. The overhead is higher in proposed compared to SAMQ in lower vehicle density is due to clustering and routing finding process, but SAMQ overhead increased for higher vehicle density.

Varying the vehicle density, the average end to end delay for packet delivery is measured and the result is given in Fig. 4.

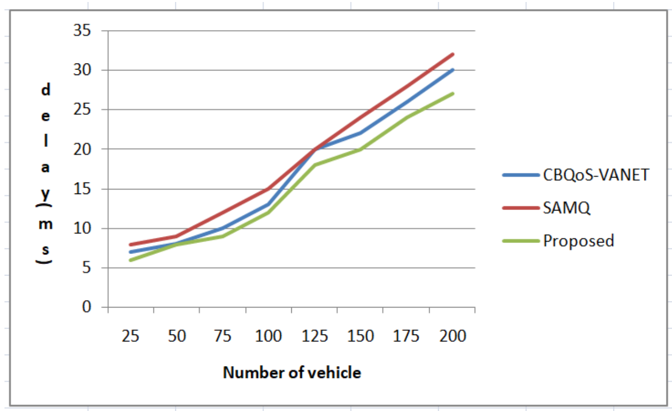

Fig. 4. Delay.

As seen from Fig. 4, delay increases with higher vehicle density. The average end to end delay in proposed solution is 9.67% lower compared to CBQoS-VANET and 19.35% lower compared to SAMQ. Service differentiation and flow control has reduced the average end to end delay in the proposed solution.

Varying the vehicle density, throughput is measured and the result is given in Fig. 5.

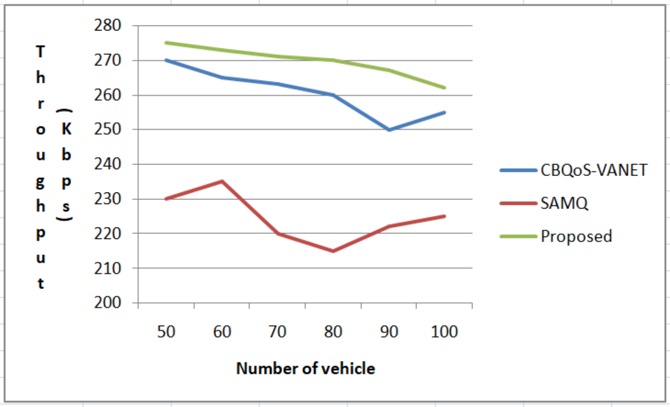

Fig. 5. Throughput.

As seen from Fig. 5, throughput reduces with higher vehicle density. The average throughput in proposed solution is 3.51% higher compared to CBQoS-VANET and 16.85% higher compared to SAMQ. The throughput has increased in proposed due to consideration of QoS constraints both during clustering and routing.

Varying the speed for 100 vehicles, the packet delivery ratio is measured and the results are given in Fig. 6.

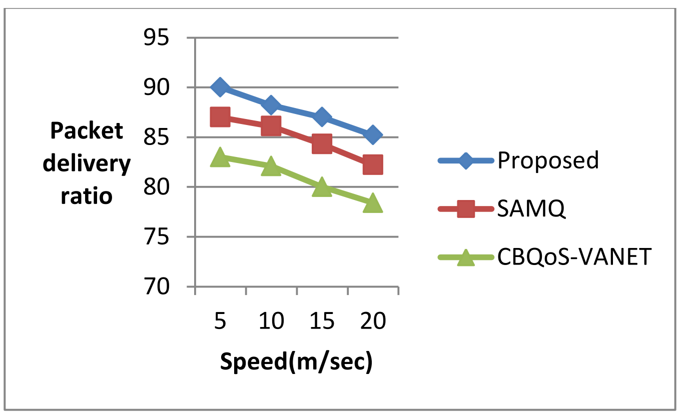

Fig. 6. Packet delivery ratio vs speed.

The packet delivery ratio is higher in proposed even as the speed increases. The average packet delivery in proposed solution is at least 3% higher compared to SAMQ and 7.6% higher compared to CBQoS-VANET. The higher packet delivery ratio in proposed solution is due to selection of more stable cluster head and effective routing path for forwarding the packet. In addition, the service differentiation based source rate control limits the packets during congestion and this helped to improve the packet delivery ratio even more in proposed solution.

Varying the speed for 100 vehicles, the packet delay is measured and the results are given in Fig. 7.

The delay is lower in proposed solution compared to existing works. It is on average 13% lower compared to SAMQ and 9.4% lower compared to CBQoS-VANET. The delay has reduced due to reduction of congestion and retransmissions due to congestion in the proposed solution. This was achieved using service differentiated control of source rate of packets.

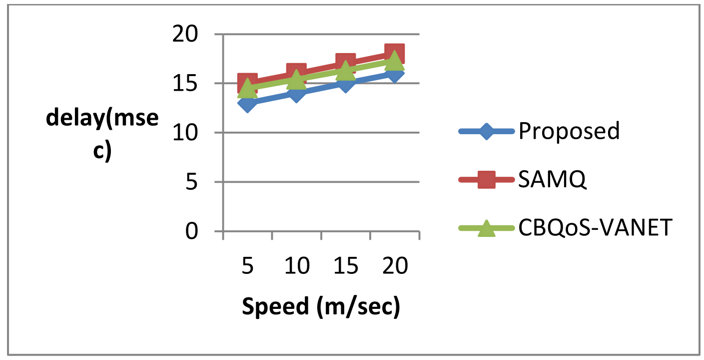

Fig. 7. Packet delay vs speed.

The optimization performance of the proposed hybrid metaheuristics is measured in terms of best value and worst value for the fitness function for six different network configurations (vehicle density). The performance is compared against PSO, Firefly and genetic algorithm and results are given in Tables III and IV.

TABLE III. BEST VALUES OF FITNESS FUNCTION

No of vehicles	Fitness Function			
	PSO+Firefly	***PSO***	***Firefly***	***GA***
50	4.72E+04	3.12E+08	1.86E+09	3.40E+06
60	2.62E+02	2.68E+10	7.11E+10	3.39E+06
70	3.04E+02	4.06E+04	3.79E+05	4.25E+02
80	4.00E+02	3.55E+03	1.09E+04	4.33E+02
90	6.06E+02	6.34E+02	6.44E+02	6.21E+02
100	7.00E+02	9.30E+02	1.56E+03	7.02E+02

TABLE IV. WORST VALUES FOR FITNESS FUNCTION

No of vehicles	Fitness Function			
	PSO+Firefly	***PSO***	***Firefly***	***GA***
50	1.62E+07	5.57E+08	5.27E+09	5.47E+07
60	1.55E+04	4.18E+10	1.14E+11	3.63E+06
70	1.01E+03	5.94E+04	1.60E+08	5.12E+04
80	5.80E+02	6.44E+03	3.30E+04	6.44E+02
90	6.17E+02	6.39E+02	6.53E+02	6.30E+02
100	7.01E+02	1.04E+03	2.01E+03	7.03E+02

In terms of best values and worst values, the proposed PSO+Firefly combination has better values compared to PSO, Firefly and GA algorithm. This is due to combination of both exploration and exploitation capability in the PSO+Firefly compared to their usage in separation.

A. Limitations

The proposed solution has following limitations:

- The solution was tested only for highway scenarios where directional mobility is not dynamic. The applicability of solution for city scenarios with dynamic directional mobility is yet to be tested.

- The solution made assumption on ratio of traffic distributions and data generators. Testing for realistic scenarios like peak hour periods, etc. was not considered in this work.

VII. Conclusion

An integrated approach combining swarm intelligence guided clustering/routing with service differentiated flow control is proposed in this work. Clustering is done using multi optimization hybrid metaheuristics and routing paths are found using ant colony optimization. In both clustering and routing swarm intelligence algorithms, objective functions are designed with QoS constraints. The proposed solution is able to achieve 2% more packet delivery ratio, 9.67% lower end to end delay, 3.51% more throughput compared to existing solution. Extending the solution for city scenarios and realistic traffic distributions is in scope of future work.

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