Quality of Service Aware Routing Protocol in Software-Defined Internet of Vehicles

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***Abstract*—Software-defined Internet of Vehicles (SDIoV) has emerged as a promising field of study as it could overcome the shortcomings of traditional vehicular networks, such as offering efficient data transmission and traffic shaping in different vehicular scenarios to satisfy all the requirements of applications on the fly. Although routing solutions are lightly addressed for SDIoV, there are many limitations of routing protocols unaddressed in such environment. More precisely, shortest path routing algorithms are mostly focused in the state of the arts. This paper presents quality of service aware routing algorithm that forwards packets toward the most reliable and connected path to the destination. Particularly, candidate routes should satisfy metrics, such as signal to interference and noise ratio (SINR) constraint and have the highest probability of connectivity. To address these issues, we have formulated a discrete optimization problem to favor the best route among candidate paths and proposed the modified laying chicken algorithm (LCA) that results better results than the traditional approaches. We have mathematically analyzed the probability of connectivity along with the SINR metric. Moreover, a multiscore function based on traffic density and greediness factor is proposed to make intelligent decision at the intersections. Simulation results are used to validate the superiority of the proposed routing approach over the existing solutions.**

***Index Terms*—Laying chicken algorithm (LCA), quality of service, routing algorithm, software-defined Internet of Vehicles (SDIoV).**

I. Introduction

WE HAVE witnessed rapid developments in the field of connected vehicles in the last few years. These advances have been possible as a result of the tight convergence of intelligent computing techniques, vehicular networks and automotive software and hardware technologies. These emerging technologies pave the ways for future autonomous driving. Researchers from both academia and industry are working closely to develop and improve the design of autonomous vehicles that will rely on the computing and communications among cars and their decision making capabilities [1]. Connected vehicles enable several applications ranging from traffic control and management, cooperative collision avoidance, finding optimal trajectory, and lane changing assistance for smart transportation system. Software defined network for Internet of Vehicles (IoV) allows smart vehicles to adapt their operating parameters for computing and communication on the fly to enhance the overall performance

In software-defined Internet of Vehicles (SDIoV), packet routing plays an important role to make IoV applications feasible since connected vehicles rely on message received from other vehicles and/or road side unit (RSU) in a multihop fashion. Enabling multihop communication in such environment facilitates wide coverage with low number of RSUs. Routing in IoV could be done through unicast [2]–[4]. However, current wireless access standards for vehicular communications cannot satisfy the delay requirements of time-critical and emergency vehicular applications. Furthermore, existing routing solutions have shortcomings in terms of scalability and adaptability to different IoV scenarios [5]–[7]. Moreover, current vehicular network lacks a mechanism of disseminating emergency messages in a priority basis.

It is obvious that the existing state of the art solutions could not be applied directly to tackle the challenges in IoV scenarios. For instance, quality of service-aware (QoS) information dissemination in different traffic conditions and fulfilling requirements of different applications will be a daunting task. These technical challenges will hinder the feasibility of IoV deployment [8], [9]. Thus, an alternative solution is required to develop a scalable, adaptable, and robust protocol for IoV environment. Software-defined network (SDN) has emerged as a promising technology for orchestrating networks and offer new features and services. When SDN is applied in IoV by disassociating the control and data planes, the controller simply manages the network and could shape the data traffic for the specific application. Thus, in SDIoV, an optimal route selection is easier as the centralized controller has a global view of the whole network.

Manuscript received August 26, 2018; revised September 28, 2018; accepted October 6, 2018. Date of publication October 11, 2018; date of current version May 8, 2019. This work was supported in part by the National Natural Science Foundation of China under Grant 61672349, in part by the National Key Research and Development Program under Grant 2016YFE0100600, and in part by China 973 Project under Grant 2014CB340303. The work of D. B. Rawat was supported by the U.S. National Science Foundation under Grant CNS-1658972, Grant HRD-1828811, and Grant CNS-1650831. *(Corresponding author: Danda B. Rawat.)*

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Digital Object Identifier 10.1109/JIOT.2018.2875482

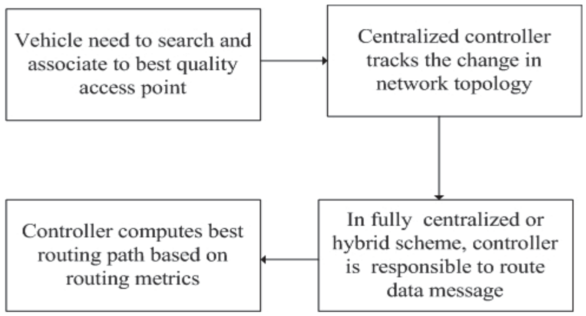


Fig. 1. Typical phases of routing in the SDIoV.

Efforts have been made to use new SDN paradigm [10] for route optimization in vehicular scenarios. In an attempt, in [11] the centralized controller uses positional and topological information in order to find best route to the destination infrastructure node. Similarly, Zhu *et al.* [12] have used the notion of SDN to efficiently forward packets toward a specified destination. In [13], the Kriging interpolation model was utilized for selecting a best RSU in terms of signal to interference and noise ratio (SINR). However, the proposed algorithm has high overhead as it extensively searches for unsatisfactory vehicles by measuring QoE of vehicles within the coverage of each RSU. In [14], a multicast algorithm was developed with an aim to reduce time latency in vehicular networks, however, the algorithm is not scalable and the complexity of the algorithm was very high. The basic steps of the multicast algorithm of [14] are summarized in Fig. 1 where to establish a route in SDN enabled vehicular network a vehicle should be associated to a RSU to send a route query. Then, a centralized controller builds a network graph based on the gathered topology information. Favoring the best quality RSU in order to send route query directly affect the performance of routing protocols. In [15], an iterative method was proposed to select the most appropriate RSU among a set of RSUs. However, this method increases the number of transmission requests to find the best RSU. To tackle the high number of transmission requests for RSU association mechanism, in [12], the Nakagami propagation model was used for this purpose. In [13], the quality of wireless channel between a vehicle and RSU was considered to judge the best RSU.

As reference to the aforementioned discussion, there are many technical challenges when developing routing algorithms in SDIoV for data dissemination. For instance, suboptimal routing might happen in case of considering shortest path routing algorithms in the controller side, when a combination of multimetrics are not considered to select optimal route for data communication and finding the metrics for route selection, which is a daunting task. To this end, this paper presents an optimal routing algorithm for data communication, named quality of service aware routing algorithm (QRA), that forward data packets toward the most reliable and connected path toward destination. More precisely, candidate routes should satisfy the metric, such as SINR constraint and have the best probability of connectivity. We have formulated a discrete optimization problem to favor the best route among candidate routes and the modified laying chicken algorithm (LCA) is proposed to solve this problem. We have mathematically analyzed the probability of connectivity by considering the SINR metric. Moreover, a multiscore function based on traffic density and greediness factor (GF) is proposed to make informed decision at the intersections in urban environment (using NS3 [16]). It is noteworthy that our proposed multihop geographical routing (GPSR) protocol is well suited for many IoV applications. For instance, in comfort-related applications, it can be used for chatting, gaming, file sharing, or infotainment between vehicles.

Specifically, our contributions in this paper are as follows.

1) In SDIoV, we have proposed a QRA—a multimetric geographic routing algorithm which uses discrete optimization with SINR and probability of connectivity—that gives the reliable and best connected route that avoids suboptimal routing in case of considering shortest path routing algorithms in the controller side.
2) LCA finds an optimal route among candidate routes between source and destination for data communication where the QRA algorithm searches for candidate routes by handshaking route discovery and reply packets.
3) We have derived mathematical model for multimetric decision that could be applied in different intersections. Furthermore, a packet carrier node considers GF and traffic density of road segment to make decision on next candidate intersection.
4) We have evaluated the performance of the proposed approach using numerical results obtained from simulations.

The rest of this paper is arranged as follows. Section II provides the literature review on recent advances of routing solutions in SDIoV. Section III presents the proposed algorithm followed by performance evaluation in Section IV. Finally, Section V concludes this paper.

II. Related Work

The issue of routing in SDIoV has been studied in various dimensions in high mobile networks. Centralized and hybrid routing are main examples of routing data packets in SDIoV. There are several research works, such as [12], [17], and [18] that use centralized routing mechanism in SDIoV. The controller has global view on the network topology and hence computes best quality path for message transmission. In such a way, controller creates per-flow route for all vehicles. In [17], centralized controller has been used to find efficient route for high data message delivery. The proposed solution is best suited for sparse vehicular traffic. However, as the proposed solution relied on complex prediction mechanism to update dynamic change of network topology, it leads to high computation delay and low throughput. Another method for dynamic update of vehicular topology is adopted in [18]. They fully relied on beacon messages to continuously update and track dynamic changing of topology. Their routing algorithm used single path per source-destination and used a Markov chain model to give priority to the routes. However, as it has high complexity, the proposed algorithm does not scale well in high density environment.

TABLE I
COMPARISON OF ROUTING SOLUTIONS IN SDIOV

Ref.	**Routing algorithm**	**RSU selection**	**Testing**	**Weakness**	**Strength / Contribution**
[20]	Eppsteins K-shortest	No	Math modeling and simulation by using NTU	Complexity and communication overhead are very high	Reliable transmission by using multipath data delivery
[18]	Not available	No	Markov modeling and simulation	Scalability is low	Priority of links is computed by using Markov chain model
[15]	Not available	The algorithm selects a RSU closest to the centralized controller	NS3 and SUMO are used for network and mobility simulation respectively	Communication overhead between RSUs and centralized controller is high	Reliable connectivity among vehicles and centralized controller
[19]	Not available	No	NS2 and Highway vehicular scenario are used	Communication overhead between RSUs and centralized controller is high	Estimation of path duration in order to find stable link (maximizing path duration) toward destination
[13]	Not available	SINR is used as a metric for RSU selection	Matlab is used for simulation	Communication overhead is high and scalability is low	Kriging model is judging best RSU
[17]	Greedy routing	No	Traffic trace is used to evaluate the proposed approach	Communication overhead is high and scalability is low	Data packet routing is cost efficient
[12]	Dijkstra	No	Packet level simulator is used to evaluate the algorithm	Communication overhead and complexity are high	Finding global optimal route from the source to the destination
QRA (Proposed)	Optimal route selection	Distance is used for RSU selection	NS3 & SUMO are used	Routing overhead are high espacially in sparse traffic conditions	Using LCA to find optimal route based on QoS parameters

Another architecture for data forwarding, different to centralized one, is adopted to SDIoV named hybrid routing mechanism. In such scheme, RSU performs as a local controller to assist the centralized controller for maintaining topology changes [13], [15], [19]. Moreover, every RSU is responsible to a specific zone within its coverage and provides any topology changes to the main controller. Then, once the centralized controller receives reports from RSUs, it builds a global view of the whole network. This mechanism significantly reduces the up-link overhead on the main controller. For instance, In [15] hierarchical SDIoV is proposed to tackle the problem of intermittent connectivity with the main controller. This is done by setting SDN zones through clustering a group vehicles within the coverage of a specific RSU. Then, those vehicles could access the main controller through cluster head and local controller (RSU). When there is no connectivity to the main controller, the RSU acts as a controller and handles all incoming traffic.

Previous studies focused on finding paths by forwarding packets toward shortest routes [15], [18]. But, they have shortcoming in terms of finding stable and reliable paths as well as more appropriate RSU to access a controller. Thus, in [20] integer linear programming is used to develop an optimized routing algorithm in order to maximize the flow rate and minimize the cost of each flow. The proposed algorithm used multiple path per source-destination, i.e., a single packet has multiple routes toward the destination. Furthermore, link lifetime and channel access parameters are used to formulate the optimization problem. However, the proposed algorithm need more additional messages, such as routing queries and replies with status beacons. Therefore, this will lead to high communication overhead. They also ignored the phase of RSU selection for accessing main controller.

Most of the previous state of the art solutions utilized the benefits of SDN in IoV scenarios by separating the control and data plane functions. This facilitate routing flexibility and ease the configuration to find optimal route toward destination. Besides, few research works have considered RSU selection phase in SDIoV. Moreover, most of the existing routing algorithms utilize static shortest path solutions, such as Dijsktra or Eppsteins K-shortest [20] in the controller for requested routing queries. However, traditional shortest path algorithm does not perform well as links are varied very fast. Thus, it is important to develop an adaptive routing algorithm that favors link quality and connectivity among vehicles during packet forwarding. Furthermore, the RSU selection mechanisms are not robust and stable as they did not consider capacity, quality of wireless channel, and distance to the RSUs. Table I illustrates main features of existing routing algorithms in SDIoV.

III. OVERVIEW OF THE PROPOSED ROUTING ALGORITHM

This section presents the proposed routing algorithm. QRA is a routing algorithm installed in the controller of SDIoV that uses LCA optimization scheme in order to compute the

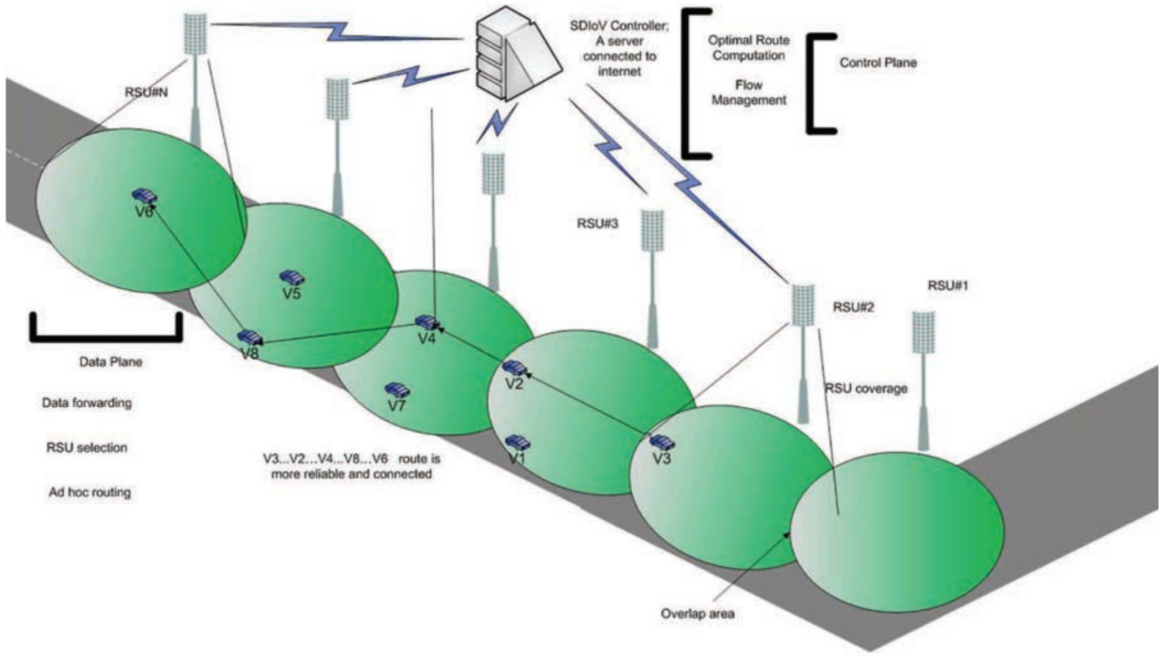


Fig. 2. Hierarchical architecture of proposed optimal routing in SDIoV.

optimal path toward the destination. The QRA favors connectivity probability and link quality. In essence, the routing procedure will begin by the source vehicle as it sends an association request to a nearby RSU. Then, upon receiving a route query from packet carrier vehicle, a controller is responsible for building network topology-based periodic beacons and making a decision on optimal path. In the proposed QRA, the network topology is build based on the reliability and quality of links. Particularly, routing metrics are used to measure the weights of links. Fig. 2 illustrates the routing process in SDIoV.

A. System Model Formulation

The developed QRA is adopted for SDIoV in which vehicles communicate with the presence of RSU. Here, we assume that all vehicles are equipped with on-board wireless access in order to facilitate communication among vehicles. We also assume vehicles are equipped with global positioning system receiver, on-board navigation system, and digital map. These facilities provide length of road segments, mobility characteristics, and location of intersections. Furthermore, vehicles could get the position of the destination by using accurate location service.

QRA finds more reliable and connected route while fulfilling the SINR_{th} constraint in urban SDN-based vehicular scenarios. Urban vehicular scenario is represented as graph model $G(i, e)$ where i is an intersection and e is the road segment between two intersections. Therefore, each optimal route ζ consists of a set of intersections $(i_1, i_2, i_3, i_4, i_5, i_6, \ldots, i_m)$ and a set of streets $(e_1, e_2, e_3, e_4, e_5, e_6, \ldots, e_n)$, where $n = m - 1$. According to the aforementioned assumptions, the objective function of the QRA optimization problem can be written as

$$\max_{\zeta} \; F(\zeta) = \lambda_1 \times \text{PC}(\zeta) + \lambda_2 \times \text{SINR}(\zeta) \tag{1}$$

where $\text{PC}(\zeta) = \prod_{i=1}^{n} \text{PC}(e_i)$

$$\text{SINR}(\zeta) = \frac{\sum_{i=1}^{n} \text{SINR}(e_i) - \sum_{i=1}^{n} \text{SINR}_{\text{th}}(e_i)}{\sum_{i=1}^{n} \text{SINR}(e_i)} \tag{2}$$

$$\text{subject to} \;\; \text{SINR}(\zeta) \geq \text{SINR}_{\text{th}}(\zeta) \tag{3}$$

where $F(\zeta)$ is defined as the objective function with a set of routes ζ from source to destination. λ_1 and λ_2 are the weights that empirically set in the simulation and their summation is equal to 1. $\text{PC}(\zeta)$ and $\text{SINR}(\zeta)$ connectivity and reliability of routes, respectively. $\text{PC}(e_i)$ and $\text{SINR}(e_i)$ representing the street's connectivity and link reliability.

B. Controller Decision on Intersection Selection

In an urban environment with IoV, intersections are involved in the routing process toward the destination. In case of not considering intersections for packet forwarding, packets might face local maximum dilemma during forwarding. Thus, this section presents main/local controller decision on first preferable next intersection for optimal routing. Then, vehicles by themselves will take over the responsibility to make decisions at the next intersection. Therefore, to build smart decision on the controller side, we introduce the input parameter of the score function: GF and connectivity metric of neighboring intersections to the current intersection.

1) *Greediness-Factor (GF):* When a packet carrier vehicle want to send data to the destination, it will send route query to the associated RSU. The RSU computes GF which indicates the closeness of a neighboring intersection to the destination intersection. Particularly, GF is D_{RSU}/D_i; where D_i is the distance of a neighboring

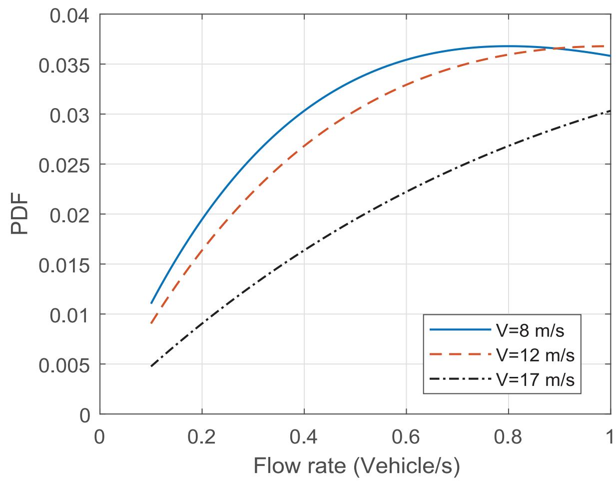


Fig. 3. Traffic density distribution with respect to the flow rate at three different vehicle speeds.

intersection to the destination intersection and D_{RSU} is the distance of the RSU (local controller) to the destination. The greater the GF is, the higher priority an intersection has, and hence shortest path will be selected toward the destination.

2) *Traffic Density (C):* Traffic density of neighboring intersections to the current one is another significant metric to ensure connectivity between intersections. This feature gives higher priority to the intersections with best connectivity. C depends of the vehicular density which is defined as probability distribution function (PDF) for distance among vehicles

$$S(d) = \lambda_n e^{-\lambda_n \times d} \tag{4}$$

where d is intervehicle distance, λ_n is, the traffic density, defined as $\lambda_n = \lambda/V$, where λ is the traffic flow rate and V is the average velocity between intersections. Fig. 3 shows the probability density function of traffic distribution with respect to the flow rate of vehicles. As can be seen, when vehicles are traveling with higher speed, the denser traffic distribution is observed.

A multimetric score function is used to aggregate the aforementioned metrics. Consider ρ_k is the kth forwarding metrics as $\rho = \{\rho_1, \rho_2, \rho_3, \ldots, \rho_k\}$ and used in a maximized multimetric function. For instance, ρ_1 is defined as GF and ρ_2 represents C. In order to rank neighbor nodes, source node has minimum and maximum range for each forwarding metric as $[\rho_k^{\min}, \rho_k^{\max}]$. Then, a general multimetric function is defined in

$$F(\rho_1, \rho_2, \ldots, \rho_k) = x \times \rho_1^{\alpha_1} \times \rho_2^{\alpha_2} \times \rho_3^{\alpha_3} \times \cdots \times \rho_k^{\alpha_k} + y_{\max} \tag{5}$$

where x is the weight to balance the value of function. To illustrate, the variable x is used to restrict the value of function $F(\rho_1, \rho_2, \ldots, \rho_k)$ to be <= one. Moreover, α_k is the k_{th} weighting factor for each routing metric. For decision on next intersection selection, the proposed algorithm uses α_1 and α_2 as weighting factors for GF and C, respectively

$$F\big(h_, e_i\big) = x \times \mathrm{GF}^{\alpha_1} \times C^{\alpha_2} + y_{\max} \tag{6}$$

Algorithm 1 QRA Mechanism

t_v: route update time interval in controller
NS: source ID
ND: destination ID
Using equ. (6) to find best candidate intersections toward destination
NS send route query to the nearby controller for global route (GR)
if *GR exist* & *currentsimtime* − *updateinterval* $\leq t_v$ & $SINR(\zeta) \leq SINR_{th}$ **then**
  an association response is sent back to the NS
else
  the controller broadcast that route query to local controllers for a specified destination
  if *GR exist in another* (*RSU*) & *currentsimtime* − *updateinterval* $\leq t_v$ & $SINR(\zeta) \leq SINR_{th}$ **then**
    an association response with a route is sent back to the NS
  else
    the controller implements optimal route discovery algorithm (refer to Algorithm 2)
  end if
end if

where

$$x = \frac{-y_{\max}}{\mathrm{GF}_{\max}^{\alpha_1} \times C_{\max}^{\alpha_2}}. \tag{7}$$

C. Optimal Route Establishment

In this section, we present the process of optimal route discovery from nearby controller to the destination. Finding optimal route toward destination is formulated as discrete optimization problem. As LCA is developed for continuous optimization problem, we used utilized modified LCA [21] to solve the such discrete optimization problem in high dynamic vehicular environment.

As can be seen in Algorithm 1, when a packet carrier vehicle needs to send data packets to a specified destination, the source sends route query packet to the nearby RSU in order to reach a controller in SDIoV. The header of the route query packet includes the source and destination ID. If the route to the specified destination exist in the controller and it is up-to-date, the controller provides a path to the vehicle; otherwise the controller will send route query to nearby local controllers. In case, the route does not exist in nearby RSUs, QRA searches starts the process of optimal route discovery as illustrated in Algorithm 2.

The controller starts the mechanism of route discovery by sending a set of egg route discovery (ERD) packet toward the destination (Algorithm 2). When ERD reaches the intersection, it records the intersection ID and the current road segment SINR then an ERD carrier vehicle at the intersection will select next intersection based on GF and traffic density (C) of road segments for neighboring intersections.

When ERD reaches the destination and all road segments SINR was greater than total $\mathrm{SINR}_{\mathrm{th}}$, this route is considered

Algorithm 2 QRA Route Discovery Mechanism

NextI: Next intersection
NS: source ID
ND: destination ID
temp path: existing path
path: optimal route
Egg Route Discovery packet: ERD
Egg Route Reply packet: ERR
Sequence of Intersections: I
Controller ID: CID
Upon receiving ERD (CID,NS,ND,I) from controller
if $N_i == ND$ **then**
  path=temp path
  send back ERR(NS,ND,I)
  Return
end if
if *ERDnotseenbefore* **then**
  add I_i *ID in the ERD packet*
  Use equ. (6) to select next intersection
  complete forwarding process to *NextI*
end if
if NextI==destination intersection **then**
  if $SINR(\zeta) \geq SINR_{th}$ **then**
    Copy the content of ERD to ERR
    traverse the same I in reverse direction toward NS
  else
    drop ERD
  end if
end if
if NextI==source intersection **then**
  store the path
  find optimal route based on equ. (1) and Laying Chicken Algorithm (refer to Algorithm 3 for LCA)
  update controller with optimal path
  route data packets toward destination
end if

as a more stable and reliable route toward the destination. Then, QRA will copy the content of ERD to the egg route reply (ERR) packet and it will traverse the same path, but in reverse direction toward the source. In some network conditions, no route will fulfill the SINR condition of (1) due to unreliable and fast wireless channel variation among vehicles. In this situation, route establishment process will be reinitiated.

QRA employs the ERR packet to make decision on optimal route selection among a set of paths toward destination. When there is a group of ERR received by the source, LCA is applied to find an optimal available route. Then, a local controller send a positive route reply to the source for commencing packet routing process. The quality of a path depends on probability of connectivity of each road segment and total SINR of the route toward destination. Upon receiving route reply from a controller, a source starts copying a route to the header of data packet and start sending it.

Algorithm 3 LCA Procedure for Discrete Optimization Problem

(x_0, y_0): initial feasible solution
(x_{best}, y_{best}): optimal solution
iter: number of iterations
Nup: Number of population
$kx = 1$
while $kx < iter$ **do**
  the population near (x_0, y_0) is generated
  (x_0, y_0)=(x_{best}, y_{best})
  for $i = 1 toNup$ **do**
    if objective function value > objective function value at (x_0, y_0) **then**
      (x_{best}, y_{best})=(x_i, y_i)
    end if
  end for
  $(x_0, y_0) = (x_{best}, y_{best})$
  $kx = kx + 1$
end while

D. Laying Chicken Algorithm for Discrete Optimization Problem

As mentioned in the previous section, when a group of ERR packets received by the controller, a set of paths from source to destination are candidate for packet forwarding purpose. Such discrete optimization problem is solved by LCA [21], which uses behavior of laying chicken on eggs to produce nests. Similar to the conversion of eggs to the chicken, LCA converges from feasible to optimal solution. In essence, each egg represents feasible solution in discrete optimization problem and a chicken is optimal solution. LCA, Here, hens try to warm their eggs in order to convert eggs to chicken. Likewise, cost of the objective function in (1) is the temperature of the eggs (routes). The higher the temperature of specific egg (route), the higher the cost of objective function for specific route. Algorithm 3 shows the mechanism of selecting optimal route among a set of candidate paths.

The algorithms starts with selecting initial feasible solution. This solution (x_0, y_0) is randomly selected among candidate routes. Then, initial population is generated near the initial solution. In case objective function value is greater than this value at (x_0, y_0), then new value is substituted in the $(x_{\text{best}}, y_{\text{best}})$. Thus, this process will continue until optimal route with highest cost is found. Next section analyzes the probability of connectivity and SINR metrics for optimal route selection in SDIoV.

E. Probability of Connectivity Model

In this section, we present a communication model for deriving connectivity probability among vehicles embedded with Internet. As shown in Fig. 2, we assume vehicles are traveling on the roads with random movement and following Poisson distribution on the roads.

In vehicular environment, vehicles are traveling with very high speed the wireless channel between vehicles are varying in a very fast pace. In the other words, vehicles are susceptible to severe fading and shadowing. Among propagation loss models, probabilistic Nakagami distribution [22] is widely used by many researchers as wireless channel model because it is empirically shown in real test-beds [23]. Therefore, The probability density function (PDF) of instantaneous received power, with parameters of k and ω, by a specific vehicle can be represented by

$$f_{p(r)} = \frac{1}{\Gamma(k)} \times \left(\frac{k}{\omega}\right)^k \times r^{k-1} \times e^{\left(\frac{k}{\omega}\right)r} \tag{8}$$

where $\omega = E(r^2)$, k is a fading figure that represents the harshness of the wireless channel, gamma function $\Gamma(.)$ is defined as

$$\Gamma(k) = \int_0^\infty z^{k-1} e^{-z} dz. \tag{9}$$

From (8), we can compute cumulative distribution function (CDF) when the received power P is greater than a threshold defined as p_{th}

$$\text{CDF}_{p(r)} = 1 - P(P \geq p_{\text{th}}) = 1 - \int_{p_{\text{th}}}^\infty f_p(r) dr. \tag{10}$$

Substituting (8) in (10), the CDF can be written as

$$\text{CDF}_{p(r)} = 1 - \int_{p_{\text{th}}}^\infty \frac{1}{\Gamma(k)} \times \left(\frac{k}{\omega}\right)^k \times r^{k-1} \times e^{\left(\frac{k}{\omega}\right)r} dr. \tag{11}$$

Here, it is necessary to find the relationship between incomplete and complete gamma function as follows:

$$P(P \geq p_{\text{th}}) = \frac{\Gamma(k, k/\omega \times p_{\text{th}})}{\Gamma(k)}. \tag{12}$$

In IoV scenarios, while vehicles are communicating with each other/with the RSU, transmitted signal power interferes with other ones. Thus, N_{th} vehicles produce $I1_{\text{th}}$ interference in Nakagami wireless channel representation. Similarly, $I2_{\text{th}}$ interference is generated by R_{th} RSUs. Moreover, the power value of the $I1_{\text{th}}$ and $I2_{\text{th}}$ is a random variable follows gamma distribution as $G(k_I, \omega_I)$. k_I affects the fading rate interference signal power while ΓI represents mean power of interference signals generated by vehicles and RSUs. As a result, total interference power is defined as follows:

$$I = \sum_{i=1}^m I_i. \tag{13}$$

The interference signal power also follows gamma distribution $I = G(k_I, \omega_I)$. The PDF of interference power is shown as follows:

$$f_{I(r)} = \frac{1}{\Gamma(k_I)} \times \left(\frac{k_I}{\omega_I}\right)^{kI} \times r^{k_I-1} \times e^{\left(\frac{k_I}{\omega_I}\right)r}. \tag{14}$$

The quality of wireless link among vehicles tightly depends on the SINR, which is defined as a ratio of signal to interference and noise power. In vehicular scenarios, vehicles exchange the value of SINR through periodic beacon frame. The value of SINR for each received packet should be greater than a specified threshold of SINR (SINR_{th}). Thus, in this case, the per-link connectivity (P_L) is calculated for vehicles within the same transmission range as follows:

$$P_L = P(\text{SINR} \geq \text{SINR}_{\text{th}}) = P\left(\frac{P}{P_l(d) \times (I + P_n)}\right) \tag{15}$$

where P_n is a noise power, $P_l(d)$ is the path loss at distance d between two vehicles, I is defined as interferences power and P represents the transmission power.

As mentioned, the power of received signal follows gamma distribution as $P = G(k, \omega)$. Furthermore, the power of the interference that affect receiving vehicles follows the distribution of $IG(k_I, \omega_I)$, and number of vehicles that are transmitting is N_{th}. Therefore, probability of connectivity per hop is computed based on (12), (14), (17)

$$P_L = \frac{\left(\frac{k_I}{\omega_I}\right)^{k \times N_{\text{th}}}}{\Gamma(k) \times \Gamma(k \times N_{\text{th}})} \times f_{I(r)}. \tag{16}$$

By substituting (14) into (17)

$$P_L = \frac{\left(\frac{k_I}{\omega_I}\right)^{k \times N_{\text{th}}}}{\Gamma(k) \times \Gamma(k \times N_{\text{th}})} \times \int_0^\infty r^{k_I \times N_{\text{th}} - 1} \times e^{\left(\frac{k_I}{\omega_I}\right)r} \times \Gamma(k, k/\omega \times (r + P_n) \times \text{SINR}_{\text{th}}).$$

F. Link Quality Derivation

IoV is a harsh environment as vehicles are traveling with high speed. This leads to high wireless channel variation. Hence, realistic channel among vehicles is prone to packet error. Therefore, SINR is considered as important metric to judge the quality of links and successful packet reception. The SINR value for a vehicle is computed as follows:

$$\text{SINR} = \frac{P_i}{P_L(d) \times (I + P_n)} \tag{17}$$

where P_n is the noise power, P_i is the transmission power and I is the interference power that affect the transmission signal power of a vehicle. $P_L(d)$ represents the path loss [24] between source and receiving vehicles and is defined as follows:

$$\text{PL}(d)[dB] = \text{PL}(d_0) + 10 \times \upsilon \times \log \frac{d}{d_0} + X_\sigma \tag{18}$$

where $\text{PL}(d)$ is the path loss at distance d between transmitter and receiver, $\text{PL}(d0)$ is the average path loss at a reference distance is $(d0)$, υ is the path loss exponent and X_σ is a zero mean Gaussian distributed random variable with standard deviation σ. The values of path loss exponent $\upsilon = 2.8$ and reference distance $d_0 = 0.4$ are used for the shadowing propagation model.

IV. Performance Evaluation

In this section, we evaluate the proposed QRA algorithm in urban IoV scenarios. The simulation is carried out using NS3 packet level simulator. It is designed according to the TCP/IP communication protocol architecture. A segment of Montreal down town is used to simulate urban vehicular scenario. The area of 9200.63 m × 5717.06 m is configured in the simulation (Fig. 4). Simulation of urban mobility (SUMO) [25] is used as

Fig. 4. Map of the region of Montreal city used in the simulation scenario.

TABLE II
SIMULATION PARAMETERS

Parameters	**Value**
Simulation time	500 s
Simulation area	9200 m $\times$ 5717 m
Mobility model	SUMO
Traffic Density	50-550 nodes
Vehicle velocity	50 km/hr
Transmission range	350 m
Maximum packet generation rate	18 packet/second
Maximum number of source nodes	9
Channel bandwidth	6 Mbps
MAC protocol	IEEE 802.11p
Data packet size	512 bytes
Weighting factors (λ_1, λ_2)	(0.4, 0.6)

microscopic road traffic flow for realistic simulation of vehicle's movement. SUMO has efficient vehicle following model, precise location service, and real-time traffic controller. It also has real world road features, such as speed limit and traffic light at intersections. Vehicles are entering the roads according to the real time traffic of real vehicular scenarios and paths from source and destination is randomly generated. Then, generated trace file form SUMO decides the traffic flow in NS3. Furthermore, 340 RSUs are randomly deployed according a uniform distribution within the area. It creates a full coverage of road segments since the radio communication range of IEEE802.11p is wide.

At the physical layer, we used the Nakagami propagation model [22] as it has a precise fading phenomena among vehicles. We set transmission range at 400 m for vehicles. In urban scenario, we vary traffic density 100 to 400 nodes, and they travel on the urban streets with maximum speed of 50 km/h. Moreover, the IEEE 802.11p [26] standard protocol, is used to model MAC layer. The simulation key parameters are summarized in Table II ([27]).

For benchmarking with the existing routing solutions, the proposed QRA is compared with the state of the arts GPSR [28] for traditional vehicular networks and SDIoV representative routing solution named centralized routing protocol (CRP) [12]. We now briefly explain the operation of these routing solutions: GPSR uses location of vehicles to greedily forward packets to a neighbor node (greedy mode of packet forwarding). In the perimeter mode, a node forwards packets to the next neighbor node by applying right hand rule; CRP uses routing server and client (vehicle) concept to exchange route query and reply. A source sends a route query packet to the routing server for specific route to the destination (e.g., [29]). Routing server utilizes network state vector and digital map to computes shortest path from source to the destination. When the route response is received by the vehicle, it copies the route entry will be inserted in its routing table and starts the process of packet forwarding.

The routing protocols are compared based on the following evaluation metrics.

1) *End-to-End Packet Delivery Ratio (PDR):* It is defined as number of successful packets received to the number of packets transmitted.
2) *End-to-End Delay:* It measures the average time delay required to transmit all data packets from source to the destination. The packet delay obtained in the simulation is the sum of sending buffer, medium access (packets delay due to interface queue), retransmission, decision at the intersection, and propagation delay.
3) *Routing Overhead:* It is defined as communication overhead generated by sending extra routing packets per successfully received data packets.
4) *Controller Overhead:* It measures the average handshaking times between vehicles and the controller.

In the performance evaluation, we conducted different experiments to study the effect of various parameters on the proposed protocol and the representative of the standard routing protocols.

A. Impact of the Weighting Factors λ_1 and λ_2

This section presents the experiments of analyzing the sensitivity of λ_1 and λ_2 of PC and SINR metrics for optimal routing toward destination. Furthermore, we conducted experiments for different values of the weighting factors. In Fig. 5, we illustrate the packet delay with respect to the simulation time for various value set of weighting factors.

As illustrated in Fig. 5, when the weighting factors (λ_1, λ_2) have the same value, the average data packet delay is lower.

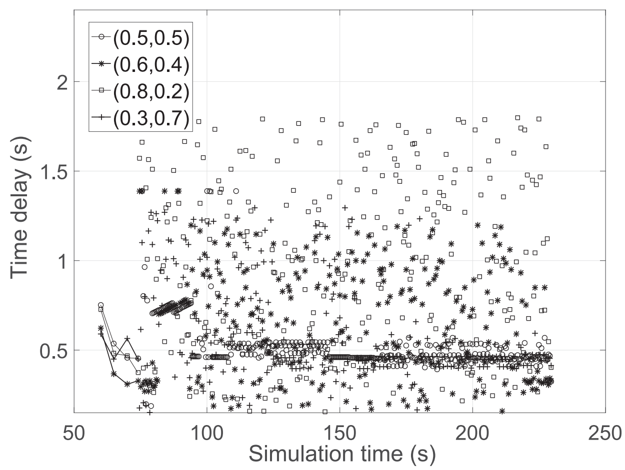
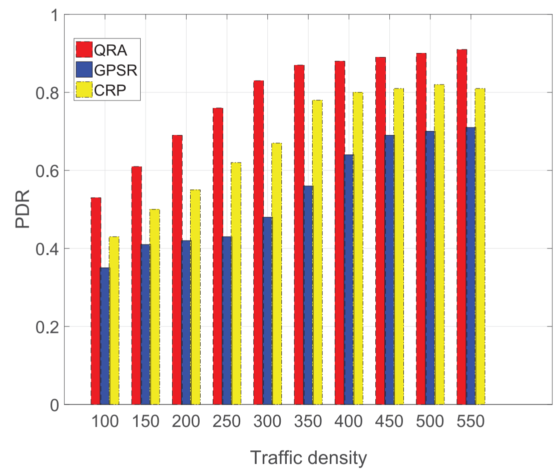
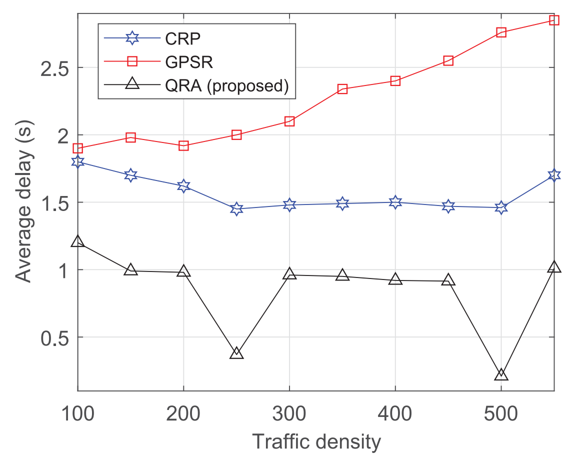


Fig. 5. Impact of weighting factors on the performance of QRA algorithm for various (λ_1, λ_2); (0.3, 0.7), (0.8, 0.2), (0.5, 0.5), (0.6, 0.4).



(a)



(b)

Fig. 6. Effect of varying number of vehicles on the performance of QRA (proposed approach), GPSR and CRP approaches for delay. (a) PDR comparison among proposed QRA and others. (b) Average packet delay.

Thus, we set the value of (λ_1, λ_2) to (0.5,0.5). This is because suboptimal routing might happen when only a single metric is considered during packet forwarding. The QRA favors more connected and reliable candidate route without giving priority to any metric. In other words, both PC and SINR are crucial in order to find optimal route in SDIoV. This can be done by setting (λ_1, λ_2) to (0.5,0.5). For example, when QRA favors SINR than PC ((λ_1, λ_2) to (0.3,0.7)), which offers high average delay of 0.836925 s. The reason is that PC contributes in finding more connected and stable route. Similarly, SINR is also has significant contribution in finding optimal route as it assures reliable route toward destination. Moreover, we observe a instantaneous fluctuation in the time latency. This might happen due to availability of the requested route in the local and main controller. More particularly, when the controller positively responses to the route inquiry, the time delay for route discovery is very low.

B. Impact of Traffic Density

In this experiment, simulations are carried out to illustrate the effects of vehicular traffic density on the performance of proposed QRA and existing routing protocols. In the simulation, we configured the speed of vehicles at 50 km/h and number of sources at 9 with 40 kb/s of constant bit rate (CBR) traffic. Moreover, the number of vehicles are varied from 100 to 550. We configured a server to act as a main controller and 340 RSUs are deployed in the simulation area.

Simulation results are illustrated in Fig. 6. In Fig. 6(a), successful packet delivery rate is plotted with respect to the number of vehicles. We observe that PDR for QRA, CRP, and GPSR is increasing with an increase in number of vehicles per unit area. The reason is that higher traffic density leads to higher network connectivity on the road segments. In more detailed explanation, when traffic density is adequately high, almost all routing algorithms' delivery rate becomes flat. For QRA, as number of vehicles are increasing, on one hand the contention on accessing RSU for accessing main controller is increasing and on the other hand packet forwarding in such dense environment leads more interference among vehicles. Moreover, finding many candidate routes by sending many ERDs toward destination contributes in packet collision on the wireless channel. In comparison QRA, CRP is not performing well as reliability of wireless channel and more connected road segments are not considered in their packet forwarding scheme. In realistic SDIoV, GPSR does not perform well as greedy packet forwarding is not satisfactory.

Another performance measure is end-to-end packet delay as illustrated in Fig. 6(b). We notice the average delay is consistent when number of vehicles are increasing. Particularly, when number of vehicles are 100 the average delay is higher than that in the dense traffic. We believe that in sparse scenario the probability of network disconnection is high during packet routing. We also observe low packet delay when traffic density is 250 and 500 nodes. This happens due to the availability of route in the main controller when a vehicle requested a specific route toward destination. As a result, packet delay is decreasing steeply. This case shows the advantage of software defined-based routing in vehicular networks. The packet delay of CRP, on the other hand, is larger than the proposed QRA. There are two reasons for this: First CRP does not consider

TABLE III
AVERAGE PDR, DELAY AND CONTROL OVERHEAD IN EXTREME VEHICULAR SCENARIOS

	Routing overhead $Node = 100$	*Routing overhead* $Node = 550$
CRP	0.25	2.6
$GPSR$	0.99	5.72
QRA	1.71	3.65

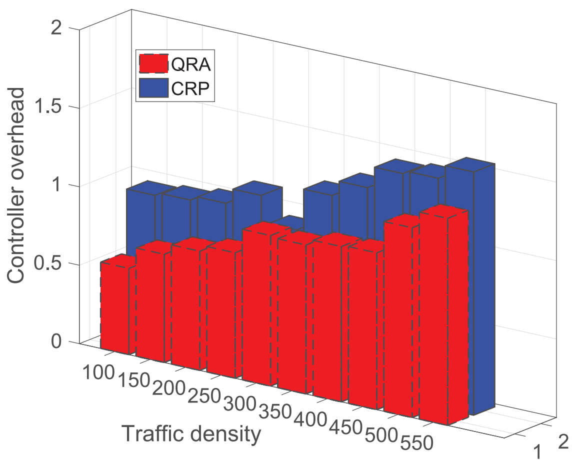
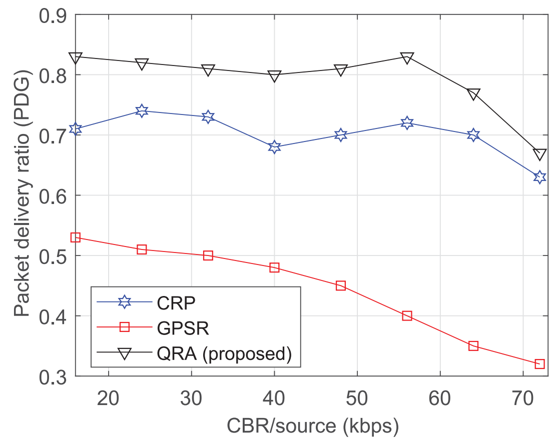


Fig. 7. Controller overhead comparison of QRA (proposed) and CRP.

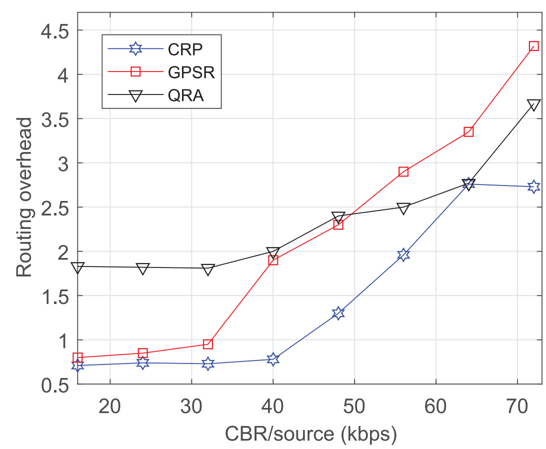
finding a set of candidate routes and select the optimal one. Second, CRP considers hop by hop optimal packet routing rather than intersection-based packet forwarding. In addition, the general upward trend of AODV is due to the fact that there is now a connected path which drives the average delay up.

Table III shows the average routing overhead according to the variation of traffic density. As we compare the proposed QRA approach in terms of routing overhead with existing solutions, we observe that the proposed QRA has slightly more overhead in comparison to the CRP. The reason is that CRP is assumed to be equipped with two wireless interfaces WiFi and WiMAX. CRP uses WiMAX in order to reach the main controller while WiFi is used for hop to hop routing. With this scheme, the routing load will be distributed on both wireless interfaces. Another reason is that QRA sends a set of ERD packets in order to find candidate routes and then it uses LCA to search an optimal path. However, our proposed algorithm offers better performance in terms of successful delivery rate and average path delay.

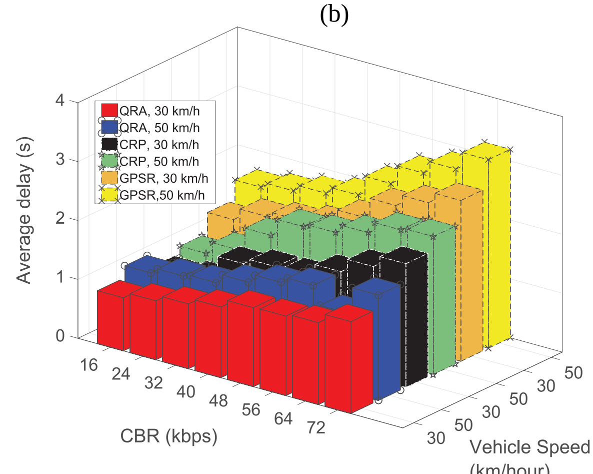
Another significant metric for performance evaluation is the communication overhead in the main controller. Fig. 7 illustrates the controller overhead variation according to the traffic density. The trend of controller overhead for QRA always lagging behind the trend of CRP. This is not surprise as QRA utilizes the benefits of local controllers (RSUs) to offer optimal route for route vehicle requesters. Moreover, QRA searches for reliable and stable path as those routes less likely susceptible to link breakdown. Thus, no extra route query is sent



(a)



(b)



(c)

Fig. 8. Effect of varying number of vehicles on the performance of QRA (proposed), GPSR and CRP approaches. (a) PDR for proposed QRA and others. (b) Routing overhead for proposed QRA and others. (c) Average packet delay.

to the main controller. The trend for both routing solution is increasing. This is due to the fact that higher number of vehicles requires higher number of route discovery request to the controller.

C. Impact of Packet Generation Rate

In this experiment, we configured traffic density on 300 nodes and number of sources on 7. To illustrate the effect of

TABLE IV
AVERAGE IMPROVEMENT OF QRA AS COMPARED TO GPSR AND CRP SOLUTIONS

	CRP	GPSR	QRA
Time delay (s)	1.56	2.27	0.85
PDR	0.679	0.539	0.787
Routing overhead	8.857	8.017	10.396

packet generation rate (CBR) on the performance of proposed routing solution, we run experiments with vehicle speed of 50 km/h.

The effect of packet generation rate on PDR is presented in Fig. 8(a). We can see that when packet generation rate is 72 kb/s, QRA, GPSR, and CRP solutions suffer a decline in successful packet delivery. The reason is that increasing the frequency of packet rate generation causes elevation of traffic load on the network, yielding higher packet contention at the MAC layer. However, PDR for CRP and GPSR are always lagging behind the QRA solution. The proposed QRA explores more reliable path for packet routing that gives better results.

Next, Fig. 8(b) presents the control overhead variation with respect to the CBR per source. As it can be seen, with a less value of CBR, an obtuse ascending of the control overhead trend is observed. This result is partly due to less traffic load on the wireless channel between vehicles. On the other hand, when the packet generation rate is increased from 15 to 72 kb/s, the trend of control overhead rises acutely. The reason is that when the CBR increases, the network load increases too, combined with the fact that this increase leads to more contention at the MAC layer. It is noteworthy that the simulator is also ran by varying the frequency of packet generation for vehicle speed of 50 km/h.

In order to investigate the impact of vehicle speed on the performance of proposed and existing protocols, the inter-packet time is varied for different vehicular speeds. Fig. 8(c) outlines the average packet delay under different CBR/source, with the vehicle speed taken as 30 and 50 km/h. As depicted in Fig. 8(c), the packet delay for all protocols increases as the frequency of packet generation rate increases for different vehicle speeds. But, GPSR suffers to a great extent from high packet latency. The performance smash of GPSR is due to the fast movement of vehicles as well as the fact that it relies on hop by hop route exploration rather than intersection-based path finding; thus, constructed routes toward destinations break down frequently. Similarly, as packet generation rate and speed of vehicles are increasing, QRA performance is decreasing. This is because generating more packets per source into the network will elevate traffic load and causes more route query and response for the controller. Moreover, we have shown the performance improvement of QRA as compared to the GPSR and CRP protocols (Table IV).

V. CONCLUSION

In this paper, we have proposed a QRA for vehicular communications in urban scenarios to find the best route for data packets by using probability of connectivity that relies on road segment and SINR parameters. The QRA has leveraged the modified LCA to find the best route among set of reliable and more connected candidate routes. Multiscore objective function has been used to select an intersection which is closest to the destination and has more connected traffic situations. The performance of the proposed approach is evaluated using extensive simulations. The numerical results have shown that the proposed QRA outperforms the existing routing solutions in terms of PDR and average end-to-end delay. The proposed QRA helps the main controller to find optimal route (not shortest path) and takes real time traffic of the streets into account. Thus, the proposed approach is suitable for real-world urban vehicular environment in which buildings and real traffics are present. Furthermore, the results have shown that the QRA can be used for applications that require reliable and stable data delivery, such as video transmission among vehicles.

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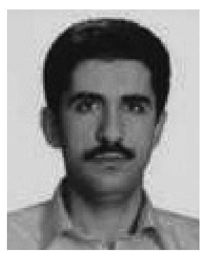

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