

# A VANET Collision Warning System with Cloud Aided Pliable Q-Learning and Safety Message Dissemination

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**Abstract:** *Ease of self-driving technological developments revives Vehicular Adhoc Networks (VANETs) and motivates the Intelligent Transportation System (ITS) to develop novel intelligent solutions to amplify the VANET safety and efficiency. Collision warning system plays a significant role in VANET due to the avoidance of fatalities in vehicle crashes. Different kinds of collision warning systems have been designed for diverse VANET scenarios. Among them, reinforcement-based machine learning algorithms receive much attention due to the dispensable of explicit modeling about the environment. However, it is a censorious task to retrieve the Q-learning parameters from the dynamic VANET environment effectively. To handle such issue and safer the VANET driving environment, this paper proposes a cloud aided pliable Q-Learning based Collision Warning Prediction and Safety message Dissemination (QCP-SD). The proposed QCP-SD integrates two mechanisms that are pliable Q-learning based collision prediction and Safety alert Message Dissemination. Firstly, the designing of pliable Q-learning parameters based on dynamic VANET factors with Q-learning enhances collision prediction accuracy. Further, it estimates the novel metric named as Collision Risk Factor (CRF) and minimizes the driving risks due to vehicle crashes. The execution of pliable Q-learning only at RSUs minimizes the vehicle burden and reduces the design complexity. Secondly, the QCP-SD sends alerts to the vehicles in the risky region through highly efficient next-hop disseminators selected based on a multi-attribute cost value. Moreover, the performance of QCP-SD is evaluated through Network Simulator (NS-2). The efficiency is analyzed using the performance metrics that are duplicate packet, latency, packet loss, packet delivery ratio, secondary collision, throughput, and overhead.*

**Keywords:** *VANETs, collision warning system, reinforcement learning, pliable q-learning, multi-attribute cost based disseminator selection, reliable safety routing.*

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## 1. Introduction

Due to the rapid smart developments of human lifestyle and vehicular environments, the usage of cars is increased day by day at every household [7]. Most people utilize their vehicles for comfortable traveling, and the vehicle population on the road is also escalated. Thereby, countless people are killed and injured by road accidents every year. By permitting more intelligent communication among the vehicles with Roadside Units (RSUs), Vehicular Adhoc Networks (VANET) saves human life and makes the journey comfortable [20]. The VANETs offer numerous active safety services such as frequent real-time traffic updating, collision warning, road conditions monitoring, and weather contexts [10]. Such safety services help drivers take timely, precise driving decisions based on disseminated safety messages, resulting in accident avoidance [29]. According to the VANET principle, the vehicles in their vicinity establish straight communication, and the vehicles in out of vicinity employ routers for data transmission [2]. Therefore, the safety messages are broadcasted in a

single or multi-hop manner. For safety message dissemination, different solutions have been introduced in the literature [11, 23]. However, the high mobility of vehicles and wireless communication medium makes the VANET message dissemination a challenging task. Moreover, the vehicle population, smart and dynamic VANET characteristics force the Intelligent Transportation System (ITS) to innovate modern dissemination techniques in the vehicular transportation system.

Collision warning is a significant application of active safety services in which the safety messages carry information about the real-time driving environment to reduce the fatalities and financial losses due to vehicle crashes [3]. The abundant data generation, inefficient router selection, and later reception of collision warning messages are the main issues of improving the collision warning systems. Modern machine learning techniques pave the way for the ITS system for innovating novel collision prediction systems [28]. As the machine learning-based collision warning system can alert the drivers

promptly by making wise decisions based on statistical learning profiles [25]. Reinforcement learning is a type of machine learning algorithm that employs optimal learning policies based on perceiving states and corresponding actions of the states with rewards from the environment. It decides the final optimal one from the long-term evaluation of cumulative rewards. The main advantage of employing reinforcement learning is the non-essential of explicit modeling of the learning environment. Albeit, the designing of Q-learning parameters is the cardinal of reinforcement learning, and it is crucial to design the Q-learning parameters based on the environmental characteristics effectively. To enhance the VANET dissemination efficiency and to save human lives, this work proposes a cloud aided pliable Q-Learning based Collision warning Prediction and Safety message Dissemination (QCP-SD). The main contributions of the proposed QCP-SD are as follows.

- To prevent the fatalities and financial loss due to vehicle collisions, the QCP-SD integrates a smart collision warning system in which the collisions are predicted in earlier and prevents the vehicle users from crashes through appropriate timely alerts.
- Initially, the QCP-SD designs the pliable Q-learning algorithm based on the dynamic VANET factors retrieved from the cloud server. The utilization of effective dynamic Q-learning parameters in QCP-SD enhances the learning accuracy, CRF estimation, and accuracy level of damage type prediction.
- To minimize the work burden at vehicles and maximizes the safety performance, the QCP-SD executes the Q-learning algorithm at RSUs and updates the dynamic Q-parameters periodically based on the information at cloud server.
- By providing alerts to the vehicles only in the risky region, the safety message dissemination of QCP-SD minimizes the overhead and maximizes the performance. For successful data dissemination, the QCP-SD disseminates messages through efficient next-hop disseminator vehicles selected using multiple parameters.
- Finally, the efficacy of QCP-SD is evaluated using Network Simulator (NS-2) Simulator. For evaluation, the different performance metrics like a duplicate packet, latency, packet loss, packet delivery ratio, secondary collision, throughput, and overhead are used.

### 1.1. Paper Organization

The remaining part of the paper is organized as follows. Section 2 surveys the works related to VANET collision avoidance. Section 3 defines the motivation and problem formulation. Section 4 comprehensively explains the pliable Q-learning based collision prediction and safety message dissemination

of QCP-SD. Section 5 shows the performance setup, metrics, and results of QCP-SD. Finally, section 6 concludes this paper.

## 2. Literature Survey

Many works have been proposed in the literature for detecting and mitigating the vehicle collisions. The works in [9, 18] surveys the collision prediction and detection methods proposed for vehicular environments. The existing works are segregated into two divisions for a comprehensive review, such as miscellaneous collision warning solutions and machine learning-based collision warning solutions.

### 2.1. Miscellaneous Collision Warning Solutions

A safety message broadcast protocol in [17] utilizes an event warning electronic control unit to disseminate the emergency alert messages to the vehicles in the dangerous region. Such protocol also controls the dissemination messages by selecting the dangerous region based on vehicle position information and bearing angle. Thus, the broadcast protocol efficiently alerts the vehicles nearer to the risky region without reducing the system performance. A multi-hop broadcast protocol for emergency message dissemination in urban VANETs has been proposed in [5]. The work in [19] proposes applying deep convolutional neural network algorithm in the autonomous vehicles traffic model design by integrating VANET with the cloud. The work in [6] proposes an efficient multi-directional data dissemination protocol known as EDDP. The main intention of EDDP is to diminish the unnecessary transmission costs without compromising the safety level of vehicles in the urban VANET environment. For better message dissemination, the EDDP only exploits fundamental data to observe the road conditions.

Further, it utilizes the location information of vehicles in a broadcast suppression strategy to reduce unnecessary dissemination. Moreover, the Efficient multi-directional Data Dissemination Protocol (EDDP) efficiently controls the dissemination overhead by considering the simple urban VANET layout characteristics and enhancing VANET safety. A context-aware system named Context-aware System for Safety Messages (CaSSaM) in [27] facilitates the VANET dissemination protocol to accomplish optimized performance by choosing adequate environmental parameters. The CaSSaM overcomes the issues of lack of environmental knowledge of existing dissemination routing protocols and assists the dissemination protocol to adapt well to the actual environmental conditions. In CaSSaM, the dissemination parameters are adjusted based on the environmental factors, resulting in high dissemination efficiency.

An Emergency Message (EM) dissemination strategy in [1] utilizes dynamic clustering and position-based cross-cluster communication methods for efficient safety message dissemination. The EM strategy constructs clusters based on primarily on interest compatibility and vehicle destination similarity estimated using vehicle position information. The EM strategy updates the position information of vehicles using the beacon messages. A time barrier-based emergency message dissemination has been proposed in [24]. Vehicle collision prediction and detection systems have been proposed for highway VANETs in [21]. The collision prediction model estimates the vehicle collision probability using an intelligent control unit. In such a model, the RSUs are responsible for tracking the vehicle information through the monitoring process. Further, it evaluates the collision probability rate based on the current vehicle status, and it disseminates warning alarms to the vehicles that are going to reach a risky zone. A Multi-Hop Broadcast Mechanism For Emergency Message Dissemination (MBM-EMD) has been introduced in [13]. The MBM-EMD employs multiple influencing factors in designing the new metric proposed for optimal hop selection. A framework in [15] consolidates the advantages of both Vehicular ad hoc nature and cloud computing structure for effective safety message dissemination. The cloud-assisted safety message dissemination framework is a downlink approach in which the traffic data is flooded using the bus gateways that are constructed with cellular and vehicle interfaces. Further, the corresponding gateway node disseminates the event message through intra vehicle communication. Thus, the framework effectively reduces the packet loss rate and broadcasts storm issues using parallel message distribution strategies.

## 2.2. Learning-based Collision Warning Solutions

The work in [8] proposes a machine learning-based lane departure warning strategy to predict the unintended behaviors of drivers during the journey. Such a model employs extreme learning to extract the driving state features. By inferring the correction possibility of drivers, the machine learning model precisely determines the unintended lane changing behaviors and alerts the drivers to prevent accidents. The work in [12] investigates the hazards in addressing the issues of applying the machine learning methods in a high-speed VANET environment. It also demonstrates that the machine learning algorithm attains better performance in diverse artificial areas. The machine learning framework also introduces the tools that assist in making decisions in VANETs. The traffic accident prediction model in [30] employs conventional neural networks to predict the accident risk probability in vehicular networks. Such a model

utilizes a deep learning strategy running at edge servers for training. Further, it extracts the autonomous features from a massive amount of collected data using the kernel tricks. Moreover, the accident prediction strategy warns the vehicles by sending an alarm through RSUs when they have a high accident risk probability value. The work in [14] designs a novel machine learning-based driving habit prediction model, named as Naive Bayesian classifier-based habitat Prediction (NBP) over VANETs. The NBP scheme uses a naive Bayes classifier to calculate the vehicle alignment status using some parameters that are relative vehicle speed, vehicle type, and traffic violation number. For effective prediction, the NBP divides the vehicles into two alignments and applies the machine learning algorithm over stable VANET clustering. Furthermore, the NBP scheme improves the VANET efficiency by making decisions using various factors like relative vehicle speed, vehicle type, and traffic violation number. Table 1 compares the existing works based on the objectives, techniques used, and advantages. Machine learning based accident prediction in [16] aims to identify the features that have high impact on vehicle accident severity. Such model utilizes various machine learning classifiers such as artificial neural networks, random forest, k-nearest neighbor, logistic regression, and decision trees to analyze the accident severity level. Further, it designs a web-based alert system based on the accident severity prediction to alert the vehicles through smart Internet Of Things (IOT) devices. A novel mechanism in [4] uses autonomous vehicles to detect the roadside anomalies automatically and utilizes the edge artificial intelligence-based communication to alert the upcoming vehicles about roadside hazards. Thus, it minimizes the accident rate at roadside considerably. It employs residual convolution neural network and visual geometry group for automatic detection and classification. However, the existing efforts employ empirical assumption parameters in collision inferring, and it is not suitable for all situations. Additionally, the prediction accuracy of existing models is not too high. The proposed QCP-SD model uses vehicle speed, acceleration, temperature, and airbag deployments in its network architecture design to predict the vehicle crashes. The change in weather conditions like rain or falling trees are not considered. Before the secondary collision to occur, it is predicted, and message is disseminated to avoid collisions it is done continuously. Since it is continuous process of prediction the period for feeling the danger is immediate and a fast responsive process. Differing from existing efforts, the proposed QCP-SD decides the pliable Q-learning parameters based on multiple influencing factors retrieved from cloud architecture and enhances the prediction accuracy of rural and urban VANET environments.

Table 1. Comparison of various existing dissemination and leaning based protocols.

Protocol Name	Description	Techniques Used	Advantages
Data Dissemination Scheme [1]	To disseminate the emergency messages in timely manner	Dynamic clustering and position-based dissemination	Minimum communication delay and improved packet delivery ratio
Time Barrier-Based Emergency Message Dissemination [24]	Aims to reduce the overhead of messages that can clutter the network	Super-node based timely dissemination	Minimize the unnecessary broadcast
Lane Departure Warning Model [8]	To identify drivers' unintended lane-departure behaviors	Extreme Learning Residual Network and Greedy LSTM	Limited false alarm rate and high accuracy
NBP [14]	To predict the driving habitat using multiple factors to form stable clusters	Naïve Byes Classifier	High cluster stability
Machine learning based accident prediction [16]	To predict the accident severity level using multiple learning methods	Web base Message alert system	Highest mean accuracy and accurate prediction
Edge artificial intelligence based novel mechanism [4]	To detect the road anomalies automatically and minimizes the accident risks	Edge artificial intelligent communication model	High classification accuracy

### 3. Motivation and Problem Formulation

Every year, 1.35 million people are killed worldwide by road traffic collisions [26] and the vehicle crashes also cause a significant economic loss to the individuals and government. Nearly 90% of accidental deaths are happened in developing countries [22]. The safer transportation is improved by utilizing the advanced collision alerts received from warning systems. Thus, the drivers take efficient and timely driving decisions based on the collision alerts, resulting in avoiding roadside hazards. The research community proposes different types of collision warning systems in which numerous kinds of roadside parameter are taking into account to improve the transportation safety system efficacy. Most of the collision warning system detects the crashes and alerts the succeeding vehicles to avoid further crashes. The learning-based collision prediction methods rectify such issues by speculating the crash possibility using various roadside features. However, the hard evaluation of local risk predictions creates some delay in sending warning messages and minimizes the system efficiency owing to inappropriate driving decisions. Also, the vast amount of VANET data generation makes the prediction and safety message dissemination as complex. Finally, an inaccurate collision warning system lacks to alert the driver with timely messages and good prediction results Thus, it increases the risk level of road users. Hence, the transportation system necessitates an effective collision warning system with optimal prediction strategies and dissemination methods. The

cloud assisted leaning based collision warning systems are an optimal solution, as they primarily aim to amplify the vehicle interactions and speed up the safety message broadcasting by maintaining the entire network information at the cloud server.

### 3.1. Network Architecture

A fundamental cloud-based VANET structure is depicted in Figure 1. The QCP-SD system consists of three major units that are vehicles, RSUs, and cloud server. The vehicles are equipped with multiple sensor devices, or humans have wearable sensor devices for safety purposes. The sensor devices continuously monitor the driving environment like vehicle speed, acceleration, temperature, and airbag deployments. The vehicle speed sensor indicates the speed level of vehicles along roadside. The vehicle acceleration sensor refers the amount of time taken by a vehicle to reach the final velocity level from the initial velocity of zero. The temperature sensor measures the road surface temperature to identify the slippery road conditions like snow, icy and slush. The airbag sensor indicates that the vehicle is deployed with airbag or not and it is triggered based on the crash severity level. The monitored information periodically reports to the cloud server via RSUs. The cloud server stores and maintains the VANET information about vehicles, drivers, and driving environments. A vehicle can receive information about other vehicles from the cloud server whenever it is needed. Additionally, incorporating machine learning solutions with a cloud-based VANET system generates appropriate alerts based on learning and maximizes the collision prediction accuracy level.

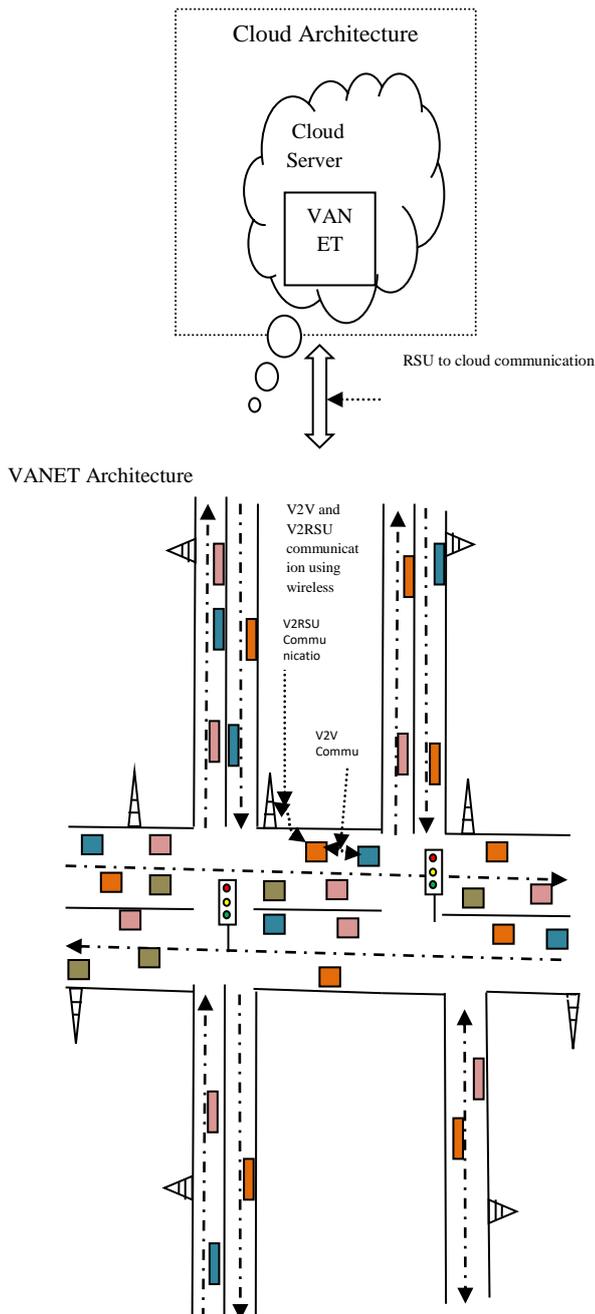


Figure 1. Cloud-VANET seamless framework model.

### 3.2. Network Model

The VANET is denoted as a network graph  $G(N, E)$ . The term  $V$  refers to the number of VANET nodes that are classified into vehicles and RSUs, where  $\{V, RSU\} \in N$ . The term  $E$  represents the straight communication links among two vehicles  $V_1 \rightarrow V_2$ . The QCP-SD considers the urban VANET environment with complex road structures, including intersections, multiple lanes, traffic lights, obstacles, and high vehicle populations. On each road, the vehicles are moving in the same and opposite directions with high mobility. The vehicles are moving at various speeds ( $V_{speed}$ ) and different directions ( $V_{dir}$ ) along the road. The direction of a vehicle is represented as  $D_r$ , and distance among two vehicles  $V_i$

and  $V_j$  are denoted as  $D_r(v_i, v_j)$ . The RSUs are fixed units placed on both sides of the roads. The communication range of vehicles ( $C_v$ ) is smaller than the communication range of RSUs ( $C_{RSU}$ ), where  $C_v < C_{RSU}$ . For effective collision prediction and warning, the QCP-SD model combines the advantages of a cloud architecture with VANET in designing the Q learning parameters. Each vehicle can obtain real-time VANET information from the cloud server anywhere through RSUs for collision risk prediction and next-hop disseminator selection. Moreover, the CRF is estimated effectively using the multiple influencing pliable Q-parameters obtained with cloud server help.

### 3.3. Problem Definition

The collision warning system is crucial in the vehicular environment as the lives of drivers and passengers depend on the driving environment. The VANET characteristics, such as the high speed of vehicles, roadside obstacles, and unpredicted driving behaviors, increase the possibility of collisions, which is very difficult to predict in real-time environments. Hence, it is crucial to design an optimal collision warning strategy with early predictions to improve the safety level of road users. This work proposes a cloud-assisted reinforcement Q-learning mechanism to predict the collision risks in a dynamic VANET environment. The main problem focused by QCP-SD is that the collision risk prediction with multiple parameters and safety message dissemination to the endangered vehicles. Most of the existing collision warning systems lack to incorporate high influencing factors in collision prediction. Also, it is very hard to maintain the vast data generation in VANET. The cloud architecture assists to handle the vast data generation and helps the vehicle to retrieve the driving environmental parameters from the cloud server at any time anywhere. The collision warning system exploits the retrieved parameters to speculate the collision risks. Unlike existing reinforcement Q-learning models, the proposed work incorporates a dynamic discount factor with the Q-learning process, named pliable Q-learning, which effectively reflects the VANET dynamicity in CRF evaluation. The main advantage of utilizing a pliable Q-learning algorithm is that it does not explicitly model the network environment. In contrast, the pliable Q-learning agent takes learning decisions based on the state actions Q-values. Instead of requiring a learning dataset with enormous VANET data, the pliable Q-learning experience-based decision making maximizes the prediction behavior of QCP-SD. Thus, the CRF based advance collision risk prediction with most influenced factors caused timely alarm to the road users and helped to take appropriate precaution decisions during driving. Further, the collision warning is disseminated based on the QCP-SD prediction results. The utilization of multi-attribute

cost value in QCP-SD disseminator selection boosts the message dissemination speed. Thus, the drivers take appropriate decisions based on the timely collision alerts and avoid the vehicle crashes.

#### 4. QCP-SD Overview

The main intention of QCP-SD is to enhance the safety level of humans and diminish the financial loss due to vehicle crashes by timely alerting the vehicles using a CRF. For that, the QCP-SD incorporates two mechanisms that are pliable Q-learning based collision risk prediction and collision alert message dissemination. The systematic design of QCP-SD is shown in Figure 2. The pliable Q-learning model evaluates a CRF value by dynamically learning the prediction factors with appropriate discount Q-values. Based on the CRF and damage type, the QCP-SD alerts the vehicles through safety alert messages. For reliable and timely message delivery, the QCP-SD utilizes a multi-cost attribute in next-hop disseminator selection.

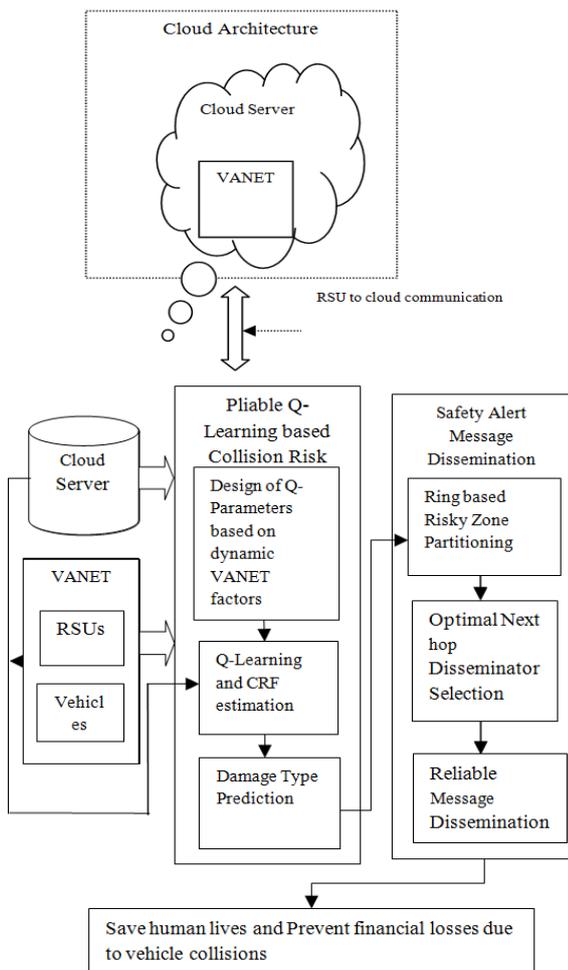


Figure 2. Systematic design of QCP-SD.

##### 4.1. Pliable Q-Learning based Collision Risk Prediction

To efficiently alert the vehicles in advance and diminish the damages due to collisions, the QCP-SD

instructs the RSUs to predict the collision risk value based on unique VANET characteristics and historical Q-learning records. The collision prediction mechanism incorporates three steps that are designing pliable Q-parameters, pliable Q-learning and CRF estimation, and damage type prediction.

**Designing Pliable Q-Parameters:** This aims to introduce a q-learning based collision risk prediction strategy that comprises four parts. In the first part, the term  $S$  is measured based on the observations of the vehicle situations at a time  $t$ . Secondly, the term  $A$  represents the discrete set of actions of the vehicles. Thirdly,  $R$  is the reward function estimated immediately based on the state and action information at time  $t$ ,  $R_t = f_r(s_t, a_t)$ . Finally,  $F$  denotes the state transfer strategies from  $t$  to  $t+1$ ,  $F = f_s(s_t, a_t)$ . In designing the Q-parameters, the QCP-SD considers the most influencing factors of causing collisions like Vehicle Speed ( $V_s$ ), Road Traffic Conditions ( $R_{TC}$ ), Complexity Level of Road ( $C_{LR}$ ), Vehicle Type ( $V_T$ ), and Weather Conditions ( $W_c$ ) as Q values,  $Q(V_s, R_{TC}, C_{LR}, V_T, \text{ and } W_c)$ . The  $V_s$ ,  $R_{TC}$ ,  $C_{LR}$ ,  $V_T$ , and  $W_c$  values are periodically updated with the help of a cloud server. The range of the influencing factor values is between 0 to 1 which is defined as a matrix shown in Equation (1). In Equation (1), the parameters are measured over a time  $t-n$  for obtaining the Q-values of vehicles. Finally, the Q values are provided as input for the Q-learning process.

$$Q_{t-n} = \begin{bmatrix} V_s(t) & V_{sf_{cr}}(t-1) & \dots & V_{sf_{cr}}(t-n) \\ R_{TC}(t) & R_{TC}(t-1) & \dots & R_{TC}(t-n) \\ C_{LR}(t) & C_{LR}(t-1) & \dots & C_{LR}(t-n) \\ V_T(t) & V_T(t-1) & \dots & V_T(t-n) \\ W_c(t) & W_c(t-1) & \dots & W_c(t-n) \end{bmatrix} \quad (1)$$

- **Pliable Q-Learning and CRF Estimation:** the core idea of the Q-learning algorithm is to dynamically update the Q-values using the following Equation (2).

$$Q(s_t, a_t) \leftarrow (1 - \phi) * Q(s_t, a_t) + \phi * f_r(s_t, a_t) + \phi Q f_s((s_t, a_t), a')$$
 (2)

In Equation (2), the term  $\phi$  is a weighting factor value that is not equal to 1. Similarly, the term  $\phi$  is a discount factor that is essential for the Q-learning algorithm. Generally, the term  $\phi$  is constant in basic Q-learning. For optimizing the learning performance and predicting the collision risk value effectively, the QCP-SD dynamically updates the  $\phi$  value based on the Q-values obtained using Equation (1). After pliable Q-learning, the QCP-SD instructs RSUs to evaluate the CRF for vehicles in its area. Each vehicle in the network and the driver has different characteristics. For instance, the vehicles are moving at different speeds with accelerations, and the unpredicted behaviors of drivers are unpredicted. Therefore, the QCP-SD considers the most five features in CRF estimation that greatly influence creating the risky events. The CRF is estimated using Equation (3).

$$CRF = CRF_{Predicted} - CRF_{Actual} \quad (3)$$

Where,

$$CRF_{actual} = [1 - (V_S * R_{TC} * C_{LR} * V_T * W_C)]_{SM} \quad (4)$$

$$CRF_{Predicted} = [V_S * R_{TC} * C_{LR} * V_T * W_C]_{Q-Learning} \quad (5)$$

In Equation (4), the term  $CRF_{actual}$  is estimated by RSUs through Straight Relative Risk Monitoring (SRRM) at current time  $t$ . Similarly, the term  $CRF_{Predicted}$  is the learning value of RSU predicted using the historical records at  $t-1$  time in Equation (5). Finally, the QCP-SD decides the CRF value using Equation (3). Incorporating most influencing VANET factors as states and taking the actions according to the states, the pliable Q-learning boosts the CRF estimation accuracy. The dynamic discount evaluation effectively reflects the VANET dynamism in collision risk evaluation. Moreover, the CRF is fed as input to the damage type prediction.

- **Damage Type Prediction:** for collision prediction, the QCP-SD segregates the CRF value of urban or rural VANETs into three types that are low, moderate, and high. Based on the CRF value, the RSU instructs the vehicles through safety messages for taking appropriate actions.

$$D_{Type} = \begin{cases} \text{if CRF} = \text{low}; & \text{only property damage will occur} \\ \text{if CRF} = \text{moderate}; & \text{property damage with injuries will occur} \\ \text{if CRF} = \text{high}; & \text{property damage and fatalities will occur} \end{cases}$$

Finally, the RSU concludes that if the CRF value is low, the vehicles will only meet property damages. If it is moderate, the vehicles will meet property damages, and humans will get injuries. Otherwise, the CRF is high, the vehicles will meet very dangerous, risky events in which fatality will occur. By predicting the collision probability using multiple severity factors, the QCP-SD effectively saves the human lives from hazardous situations and financial losses due to property damage. The RSU initiates the safety message dissemination process through ring based risky zone formation and multi-attribute cost-based disseminator selection.

## 4.2. Safety Alert Message Dissemination

The safety message dissemination process of QCP-SD involves efficiently delivering the messages to the vehicles that meet the hazardous situation. In QCP-SD, the RSU is responsible for broadcasting safety messages to the vehicles that will meet risky events based on the CRF value. Initially, the RSU forms a risky region based on the CRF damage type. After, the region is partitioned into multiple ring zones to select the optimal next hop for rebroadcasting. Finally, the collision risk message is successfully delivered to the vehicles that will meet collision.

- **Ring based Risky Zone Partitioning:** in QCP-SD, the range of dangerous zone is determined from the CRF value, damage type of collisions, road type,

and vehicle characteristics that are speed, direction, density, and location. If the RSU predicts any collision event, it inaugurates the risky zone formation process. The size of the risky zone is significantly varied based on the collision type. A type of risky zone formation scenario is depicted in Figure 3.

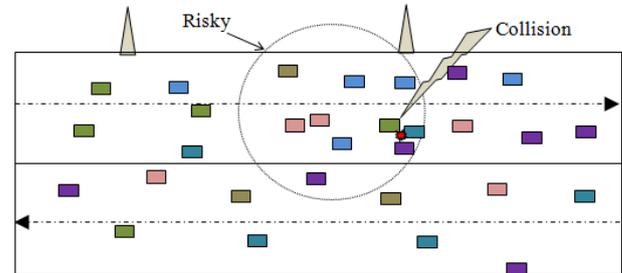


Figure 3. Risky zone formation of QCP-SD.

In Figure 3, the two vehicles in a risky zone will meet collision within a few seconds. The RSU predicts the CRF value  $D_{type}$  of such vehicles is high and initiates the safety message dissemination process. The RSU exploits two types of communication for broadcasting safety messages. In the first type, the RSUs directly alert the vehicles within its area through the safety message dissemination process. Secondly, the vehicles that are far away from RSU receive safety messages from the RSU in a multi-hop manner. The risky zone area is confirmed using the following Equation (6).

$$R_{Area} = \frac{\pi r^2}{2} \quad (6)$$

In Equation (6), the risky zone area is referred to as  $R_{Area}$ . The term  $r$  refers to the radius of the risky zone decided based on the terms  $CRF, D_{Type}, R_{Type}, V_c$ . The term  $V_c$  defines the characteristics of vehicles. Also, the vehicles are moving both directions on the road, and the QCP-SD neglects the unnecessary safety message dissemination to the vehicles in the opposite direction by considering the vehicle characteristics in risky zone formation. Further, the risky zone is separated into multiple ring zones based on Dedicated Short-Range Communication (DSRC) of vehicles. The ring zone formation is shown in Figure 4.

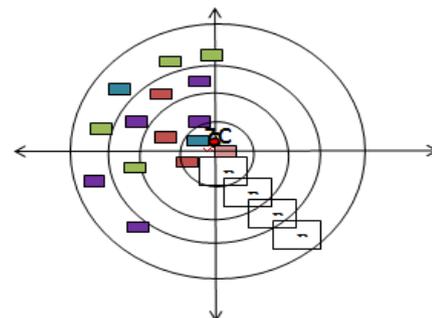


Figure 4. Ring zone formation.

For effective message delivery, the vehicles in the

Risky Zone (RZ) are divided into multiple zones like  $\{R_1, R_2, \dots, R_j\} \in RZ$ . Initially, the RSU straightly disseminates the safety warning message to the destination group  $\{G(D_1, D_2, \dots, D_n)\} \in R_1$  in its area. Further, an optimal disseminator vehicle selection process is initiated to disseminate the safety messages to the desired destination group.

Optimal Next-hop Disseminator Selection: after ring zone partitioning, the QCP-SD selects the next-hop dissemination vehicle using a multi-attribute cost value. The cost value of the vehicles in each ring is evaluated using the following Equation (7).

$$NHD_v = W_{Dr} * D_r + W_p * \text{Min}(D_{(v)RZi \rightarrow RZj}) + W_s * \text{Max}(S) + W_{ND} * N_D \quad (7)$$

In Equation (7), the terms  $D_r$ ,  $\text{Max}(S)$  and  $N_D$  refers to the direction, maximum speed, and neighbor density of the risky ring region. The vehicles moving towards the collision risk area have high weight values than the vehicles are moving in the opposite direction. Also, the destination group vehicles in  $R_1$  estimate relative distance  $D_{(v)Ri \rightarrow Rj}$  using the position information of itself to the R2 using Equation (8).

$$D_{(v)Ri \rightarrow Rj} = \sqrt{((x_j - x_i) + (y_j - y_i))^2} + \mu \quad (8)$$

In Equation (8), the position information of vehicle  $i \in R_1$  and  $j \in R_2$  is  $(x_i, y_i)$  and  $(x_j, y_j)$ , respectively, and the term  $\mu$  is the relative distance constant value. The vehicle with a high-cost value is selected as next hop dissemination vehicle and rebroadcasts the safety messages in its zone. Similarly, the safety messages are successfully rebroadcasted until they reach the desired destination group vehicles of  $R_j$ . By selecting an optimal next-hop disseminator, the QCP-SD maximizes the safety alert message dissemination efficiency and avoids nearly 60% of accidents due to vehicle collisions. The QCP-SD also utilizes simple computation mechanisms, and thus, it reduces the time delay in safety alert message delivery. Moreover, the QCP-SD prevents the fatalities and financial losses caused due to vehicle collisions by utilizing optimal deep learning-based collision prediction and an effective safety alert dissemination process. The overall algorithm of QCP-SD is explained below.

*//Protocol Design of QCP-SD//*

*Input: VANET seamless framework with dynamic network characteristics.*

*Output: Pliable Q-learning, collision risk prediction, and safety message dissemination*

*Initialize the network;*

*QCP-SD do {*

*Designing the pliable Q-parameters using cloud server;*

*Extracts most influenced factors of collision;*

*Learns the parameters using Pliable Q-learning*

*model;*

*Estimates CRF using the learning and monitoring values;*

$$CRF = CRF_{\text{Predicted}} - CRF_{\text{actual}}$$

*Collision prediction based of CRF value;*

*Predicts the  $D_{\text{Type}}$ ;*

*};*

*RSU do {*

*Forms the Risky Zone;*

*Initiate the safety alert message*

*dissemination*

*process;*

*If (vehicles are in RSU range) {*

*Straight dissemination;*

*Else {*

*Messages are broadcasted to the*

*destination group  $\{G(D_1, D_2, \dots, D_n)\} \in R_1$  using optimal next-hop disseminator;*

*For ( $v$  in  $R_j$ ) {*

*Estimates multi attribute cost*

*value;*

$$NHD_v = W_{Dr} * D_r + W_p * \text{Min}(D_{(v)RZi \rightarrow RZj}) + W_s * \text{Max}(S) + W_{ND} * N_D$$

*If (Cost of  $v$  == high) {*

*The vehicle is selected as next-hop disseminator Rebroadcast the messages;*

*}}};*

## 5. Performance Evaluation

The QCP-SD validates its efficiency through NS-2 simulation. The proposed QCP-SD protocol is compared with existing MBM-EMD presented [13] in simulation. The simulation parameters of QCP-SD are described in Table 2.

Table 2. Simulation parameters.

Network area	1Km x 1Km
Number of vehicles	90
Vehicle Transmission Range	250m
Number of RSUs	4
RSU Transmission Range	500m
Mobility model	SUMO
Maximum vehicle speed	10 to 100 Km/hr
Packet size	512 Bytes
Bandwidth	10MHz
Simulation Time	5 Minutes

### 5.1. Performance Metrics

For performance evaluation, the QCP-SD employs different performance metrics such as duplicate packet, latency, packet loss, packet delivery ratio, secondary collision, throughput, and Overhead.

- Duplicate Packet: it refers to the number of replicated packets received by a vehicle within the risky area.
- Latency: the total time taken to deliver the safety alert message to the desired destination group.
- Packet Loss: it is the number of failed packets to the total number of generated packets.

- Packet delivery ratio: the ratio of the number of successfully delivered packets to the total number of generated packets in the network.
- Secondary Collision: it is the number of secondary crashes that happened within the risky region.
- Throughput: it is the rate of successful data delivery among a source-destination pair.
- Overhead: it is the number of control packets utilized for collision risk prediction and safety message dissemination.

### 5.2. Simulation Results

The performance results are obtained by varying the node density from 30 to 90 to analyze the effectiveness of QCP-SD with different density scenarios.

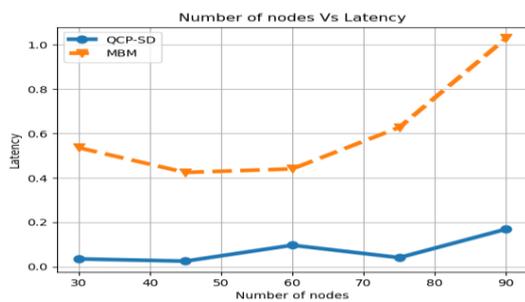


Figure 5. Number of nodes vs. latency.

Figure 5 shows the comparative latency results of QCP-SD and MBM-EMD under different node density scenarios. The QCP-SD increases the delay by varying the node density from 45 to 60. The reason is that the QCP-SD has to evaluate the multi-attribute cost function to the maximum number of vehicles under a high-density scenario. Thus, it incurs some delay in the network. After the point of 60 numbers of nodes, the QCP-SD decreases the delay suddenly. For example, the QCP-SD attains 0.09 and 0.04 seconds of latency for 60 and 75 node density scenarios, respectively. However, the QCP-SD outperforms the MBM-EMD, as shown in Figure 5. For instance, the QCP-SD and MBM-EMD accomplish latency results of 0.16 and 1.02 seconds, respectively, for a 90 node density scenario.

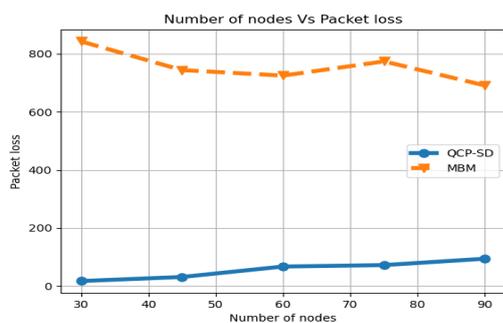


Figure 6. Number of nodes vs. packet loss.

Figure 6 plots the packet loss results of QCP-SD and MBM-EMD obtained by varying the number of

nodes from 30 to 90. The packet loss of QCP-SD is slightly increased with varying the number of nodes from 30 to 75. It is because many nodes compete to access the channel, and there is an amount of packet loss due to collisions. For example, the QCP-SD accomplishes a packet loss rate of 17 and 94 under 30 and 90 node density scenarios. However, the QCP-SD shows its superior performance under all density scenarios than the existing MBM-EMD. For example, the QCP-SD and MBM-ED attain 94 and 691 packet loss rates, respectively, when the node density is 90.

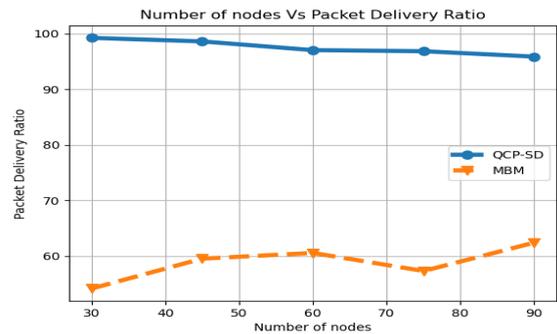


Figure 7. Number of nodes vs. packet delivery ratio.

The packet delivery ratio results of QCP-SD and MBM-EMD are shown in Figure 7. The QCP-SD decreases the packet delivery ratio by varying the number of nodes from low to high, as the huge numbers of nodes try to access the channel, and there is a packet loss due to collision. For example, the QCP-SD accomplishes 99.2% and 95.8% of packet delivery ratio, respectively, when 30 and 90 nodes are presented in the network. The QCP-SD shows superior performance than existing MBM-EMD under all density scenarios, as depicted in Figure 7. For example, the QCP-SD and MBM-EMD accomplish 95.8% and 62.4% of packet delivery ratio, respectively, when a huge number of nodes 90 presented in the network.

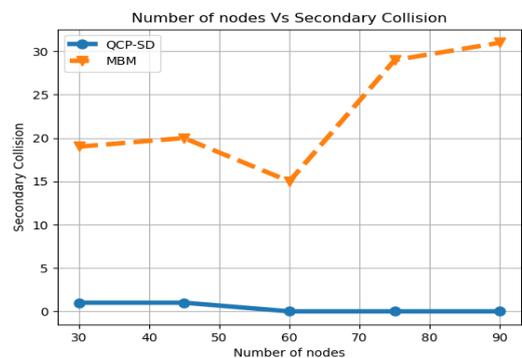


Figure 8. Number of nodes vs. secondary collision.

Figure 8 demonstrates the secondary collision results of QCP-SD and MBM-EMD obtained by varying the number of nodes from low to high. Initially, the secondary collision result of QCP-SD is due to the ineffective reception of safety alert due to

poor connectivity. In Figure 8, the QCP-SD accomplishes one secondary collision for 30 and 45 node density. After 45, the secondary collision of QCP-SD is zero, as the high density vehicles offer better connectivity and quickly deliver the safety alert messages. However, the pliable Q-learning based collision risk prediction of QCP-SD shows its enhanced performance than MBM-EMD under all density scenarios. For instance, the QCP-SD and MBM-EMD attain 0 and 31 secondary collisions for 90 node density scenarios, respectively.

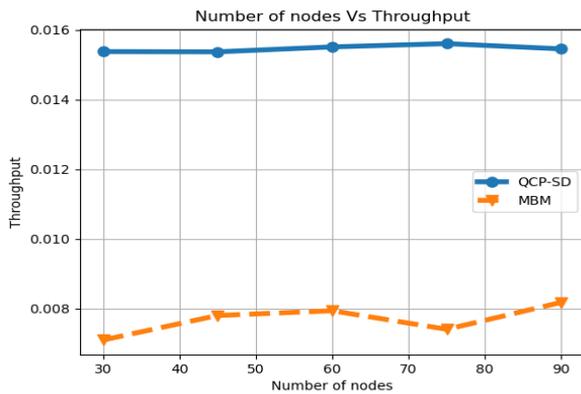


Figure 9. Number of nodes vs. throughput.

Figure 9 shows the comparative results of the throughput of QCP-SD and MBM-EMD. The QCP-SD increases the throughput from 45 to 75 node density scenarios, whereas it is slightly decreased after the point of 75. This is caused by the availability of a better next hop disseminator under high-density scenarios than low-density scenarios. After the point of 75, the network is saturated, and there is some packet loss. However, the QCP-SD outperforms the MBM-EMD under low and high node density scenarios, as shown in Figure 9. Unlike MBM-EMD, the QCP-SD utilizes a pliable Q-learning based collision prediction and multi-attribute cost-based disseminator selection, resulting in high throughput. For example, the throughput of QCP-SD and MBM-EMD is 0.015 and 0.008 Kbps for 90 node density, respectively.

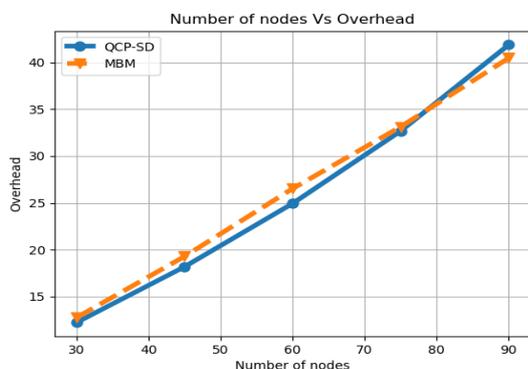


Figure 10. Number of nodes vs. overhead.

The overhead results of both ACP-SD and MBM-EMD are plotted in Figure 10. Both models increase the Overhead by varying the number of nodes from 30

to 90. The reason is that the high number of nodes amplifies the utilization of control packets under the high-density scenario. For example, the QCP-SD and MBM-EMD incur 12.2% and 12.7% of Overhead, respectively, when 30 vehicles are moving in the network. Figure 10 depicts that the QCP-SD attains much overhead than existing MBM-EMD under a high node density scenario of 90, as the nodes in QCP-SD employ control packets to obtain the real-time VANET information from the cloud server.

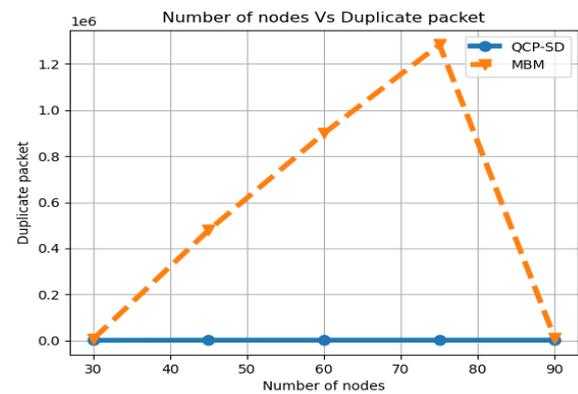


Figure 11. Number of nodes vs. duplicate packet.

Figure 11 portrays the relationship between the comparative results of the duplicate packet of QCP-SD and MBM-EMD. The QCP-SD effectively reduces the duplicate packets by designing a risky region and multi-attribute-based dissemination selection process. By partitioning the risky region into multiple rings, the QCP-SD effectively delivers the safety alert message to the dangerous vehicles at once and avoids the packet replication. For example, the QCP-SD attains 0.01 of duplicate packets under low and high node density scenarios. Unlike QCP-SD, the MBM-EMD does not form any risky region, and there is an amount of data packet replication at each node. For instance, the QCP-SD and MBM-EMD accomplish 0.01 and 1.3 duplicate packet ratios, respectively, when 75 numbers of vehicles are presented in the network.

## 6. Conclusions

In this paper, a novel collision warning system named as QCP-SD has been proposed to maximize the safety level of VANET users during driving. For effective collision risk prediction and safety message dissemination, the QCP-SD integrates two mechanisms that are pliable Q-learning-based collision risk prediction and safety alert message dissemination. The pliable Q-learning algorithm maximizes the collision prediction accuracy by considering the most influencing dynamic VANET factors retrieved from the cloud server in CRF evaluation. Further, the ring partitioning based risky zone formation and multi-attribute cost value based next-hop disseminator selection in safety message dissemination maximize the safety alert message dissemination efficiency with

minimum latency. Also, sending the safety messages only to the vehicles in risky region minimizes the message duplication rate significantly. Furthermore, the advance prediction of collisions and timely safety alerts to the vehicles in the risky area of QCP-SD avoids the fatalities and financial losses due to vehicle crashes. Finally, the simulation results show the effectiveness of QCP-SD in terms of various performance metrics. From the results, the QCP-SD accomplishes 95.8% of packet delivery ratio and 0.015 MB/s of throughput under high node density scenario. The QCP-SD accomplishes 0.01 of duplicate packet ratio and it is reduced by 99.2%, than the existing MBM-EMD protocol. The QCP-SD is extended with multiple realistic Q-parameters in future. Furthermore, the future work plans to append the security methods in safety message dissemination of QCP-SD to offer defense against different attacks.

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