Reducing Beacon Error Rate for Congestion Control in Vehicular Ad-hoc Networks through Reinforcement Learning

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Abstract- Intelligent transportation systems utilize vehicular ad-hoc networks (VANETs) to facilitate vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. Channel congestion poses a significant challenge in VANETs due to limited channel capacity and dynamically changing scenarios, particularly impacting real-time traffic. Channel congestion can obstruct transmission of basic safety messages (BSMs) for avoiding roadblocks, accidents, and other real-time scenarios. Hence most of the research are conducted focusing on controlling congestion in vehicular networks. Various parameters such as Channel Busy Rate (CBR), Inter-Packet Delay (IPD), and Beacon Error Rate (BER) are instrumental for achieving this objective. The proposed research focuses on Beacon Error Rate minimization for vehicular networks using reinforcement learning for controlling congestion. According to the research, along with Channel Busy Rate (CBR), Beacon Error Rate (BER) can be effectively used as congestion control parameter for Vehicular networks.

Keywords: *BSMs, IPD, BER, CBR, V2V, V2I, VANET.*

1. Introduction

Vehicular Ad-hoc Networks (VANETs) are a subclass of MANETs (Mobile Ad-hoc Networks) used to provide intelligent transportation [1] in road traffic scenarios. They consist of devices integrated into moving vehicles called On-Board Unit (OBU) and as well as routing devices installed road side called as Road Side Unit (RSU) [2]. Messages can be transmitted between different On-Board Units present in separate vehicles or between vehicles and Road Side Units.

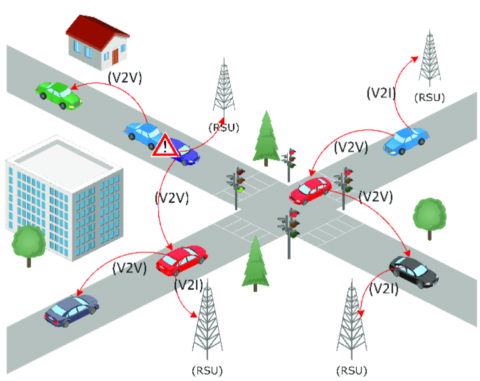

Figure 1: Nodes in vehicular networks

Hence, Vehicular Ad-hoc Networks provides Vehicle-to-Vehicle (V2V) communication and Vehicle-to-Infrastructure (V2I) communication. Vehicle-to-Vehicle [3] communication is a kind of peer-to-peer communication whereas Vehicle-to-Infrastructure enables many-many communications between the nodes.

Beacons are the messages transmitted between communicating nodes used in road traffic networks. Basic Safety Messages (BSM) [4] play a major role in detecting, avoiding different critical road traffic scenarios like accidents, traffic jams, road blocks etc.

The traffic at Road Side Units varies unconditionally since real-life traffic scenarios contain sufficient number of exceptions, sometimes they can grow unexpectedly which can lead to overflooding of beacons [5] and the communication channel may be inactive. In those scenarios, any Basic Safety Message can't be received at necessary On-Board Unit for urgent information [6]. Hence necessary support [7] to the driver can't be provided and accidents/ road blocks etc. can happen due to lack of communication from vehicular network to the driver side. This situation is known as congestion [8] in communication channel of Vehicular Adhoc Network.

Congestion increases due to increase in vehicle density and reduces transmission capability. Transmission parameters [9] are of two types: 1) transmission power and 2) message rate. To minimize congestion most researchers have targeted optimization of the parameters. Channel Busy Rate (CBR) [10], Inter Packet Delay (IPD) [11] and Beacon Error Rate (BER) [12] are different parameters to evaluate traffic congestion scenarios. Multiple studies have been conducted for controlling congestion in communication channel of vehicular networks. A major drawback of the techniques is to increase inter packet delay (IPD). A study [13] represents that optimization among parameters is a more difficult issue to address. High mobility of nodes [14] and changing environment can increase complexity of congestion issues in VANET. Hence an intelligent approach for reducing complexity of congestion problems was provided to apply decision capability of nodes [15] i.e. each node can take "right" decision to decide which safety messages to work upon.

This study focuses on using reinforcement learning [16] to manage vehicular network congestion and minimize BER [29] during vehicle-to-vehicle and vehicle-to-infrastructure communications.

2. Literature Survey

Different Machine Learning-based approaches are developed for congestion control in VANETs. A centralized and localized Machine Learning Congestion Control (ML-CC) approach based on k-means clustering was suggested [17] to evaluate message transmission congestion. Deep reinforcement learning was used to allocate V2V resources for unicast and broadcast scenarios in study [16]. Another study [15] used reinforcement learning for power regulation and rate adaptation in cellular radio access network downlinks. Another VANET V2V congestion control study [25] used decentralized reinforcement learning. Instead of environmental interaction, this RL-based technique uses feasible actions and a Nakagami model to decide the agent's next state. Another study [26] improved beacon rate selection by combining on-policy control with function approximation to generalize prior conditions and make educated selections in unexpected scenarios. Research [27] proposes RL-CDCA at the MAC layer. This decentralized collaborative method requires reward-sharing nodes to adjust channel selection and backoff window. Study [31] adjusts channel congestion with RTPC. A vehicle transmitting at a constant power and rate produces channel congestion that matches these specifications. According to the authors, concurrent packet collisions significantly affect system awareness. This method improves CBR ratio but reduces vehicle awareness. Reinforcement Learning-based application layer congestion and awareness control in Vehicular Ad-hoc Networks is understudied. We present Reinforcement Learning-based methods in this field in this paper.

3. Proposed model based on Reinforcement Learning

Reinforcement learning uses (1) Agent and (2) Environment which interact among themselves by (Action, State/ Reward) pair. In case of vehicular networks, vehicle acts as the agent which sends beacons to Road Side Units, Other vehicles, communicating nodes etc. known as environment. Since multiple beacons arrive at environment which can select appropriate action and reward in the form of basic safety messages, sent to the vehicle. Figure 2 represents Reinforcement Learning in vehicular communication.

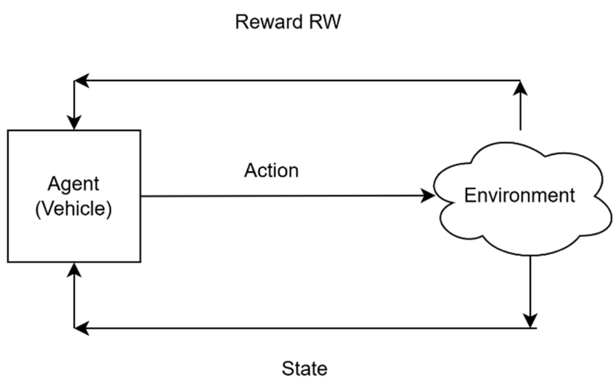

Fig. 2. Reinforcement Learning cycle in Vehicular Communication.

At t = 0, a vehicle and environment interact. In every time step (t = 0), the vehicle gets a state information for environment (S) and selects an action (A(s)) based on the representation. After each discrete time interval, the node avails a reward (RWt+1) and changes into state (S+1). The vehicle aims to optimize total reward (RWt).

γ represents discount rate which calculates current value of upcoming rewards. Gt represents the expected return for a vehicle:

$$RWt = (S_{t+1}) + (\gamma S_{t+2}) + (\gamma\ 2S_{t+3}) + \ldots = \sum_{k=0}^{\infty}(\gamma S_{t+k+1}) \qquad (1)$$

where $0 \leqslant \gamma \leqslant 1$. When γ is nearer to 1, greater prizes are possible. Vehicles learn via Reinforcement Learning by assessing whether a state or action is good. Returns determine state or action acceptance. π(a|s) maps state policies. The state-action-value function Q (s, a) determines the action value for a given state and policy. To increase efficiency, minimize Q (s, a):

$$Q_*(s,a)=\max\ [Q\ (s,a)] \qquad (2)$$

The vehicle can select appropriate action which gives it the optimized state-action value as given below:

$$\Pi_*(a\ |s\ )=\begin{Bmatrix} 1 & if\ a = argmax\ Q*(s,a) \\ 0 & otherwise \end{Bmatrix} \qquad (3)$$

a. Components of reinforcement learning framework

In this approach, vehicles make decisions based on their own observations and information received from nearby vehicles. No further communication or information exchange is needed. The available states are determined by the actions taken by each vehicle and the resulting data. The primary components of the congestion management challenge within the proposed Q-learning framework of Vehicular communication consists of Environment, Action, State and reward function.

Environment: Contains agents and their interactions. Any agent can interact with the environment and modify it as needed, but it cannot change its rules. Wireless channels and other vehicles can be used in Vehicular Network. Traffic, vehicle velocity, vehicle density, etc. are part of an uncertain environment. activities can alter the environment but not road vehicle density.

Action: It represents methods which interact with environment. VANET basically uses two actions: beacon rate and transmission power. The proposed method uses the beacon rate in this work. Assumes maximum beacon rate 10 MSM in DSRC and minimum 1 BSM. Hence there are 10 beacon levels, $a \in N, 1 \leqslant a \leqslant 10$.

State: The state represents the current environment condition, influenced by the agent's actions, which lead to transitions to new states. In this context, the state space encompasses the BER.

Reward Function: The reward function defines how an agent learns from the feedback provided by the environment following its actions, with each action's effectiveness determined by this function. The reward function can be designed in a way that meets the learning goals. Our recommended methodology is to keep the BER minimum while sending required number of SBMs.

Equation 4 represents Beacon Error Rate (BER):

$$BER = \frac{Number\ of\ lost\ packets}{Number\ of\ received\ packets} \tag{4}$$

Higher BER can lead to more congestion in the communication channel.

b. Q-learning technique

Q algorithm, uses **Off-Policy** approach which uses current action taken from the currently used policy to learn the Q-value.

Update statements for Q-learning technique can be defined as follows:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha(RW(s_t, a_t) + \gamma \max Q(s_{t+1}, a_t) - Q(s, a_t)) \tag{5}$$

Here, updating depends on the current action, current state and reward obtained, next state and current action.

The SARSA algorithm $\in$ greedy policy for updating in Q-table as per equation 5.

Algorithm

Q-learning Based Congestion Control (QBCC)

1. Let S be initial State.
2. Find current action value based on current Q value.
3. Find S' as next state for action a and reward rw.
4. Use epsilon-greedy policy to find next action a' based on the updated Q values.
5. Update the current state-action pair using the Q-update rule provided in equation (5)

There are 2 phases in congestion control.

a) Find Q table for the environment.
b) Apply the Q-Table to a traffic simulation scenario.

4.Simulation Environment

The simulation uses a software tool SUMO (Simulation of Urban Mobility) for simulation of real-world traffic scenarios. Later on, this scenario is merged with a reinforcement learning model.

This work uses the following steps in simulation

1) Download selected geographical area of the world from Open Street Map (OSM), a digitized street map, to precisely identify the boundaries and intersections of roads, in the form of OSM file.
2) A command line utility NETCONVERT was used to convert the OSM file to a network file.
3) A python utility randomTrips.py was used to generate route files.
4) Another command line utility POLYCONVERT was used to integrate polygons and edges to the route file.
5) Command line version of SUMO was used to integrate all of the above files to produce a SUMO configuration file.
6) Now the SUMO GUI was used for simulation of the SUMOCFG file. Figure 2 represents a sample sumo simulation.

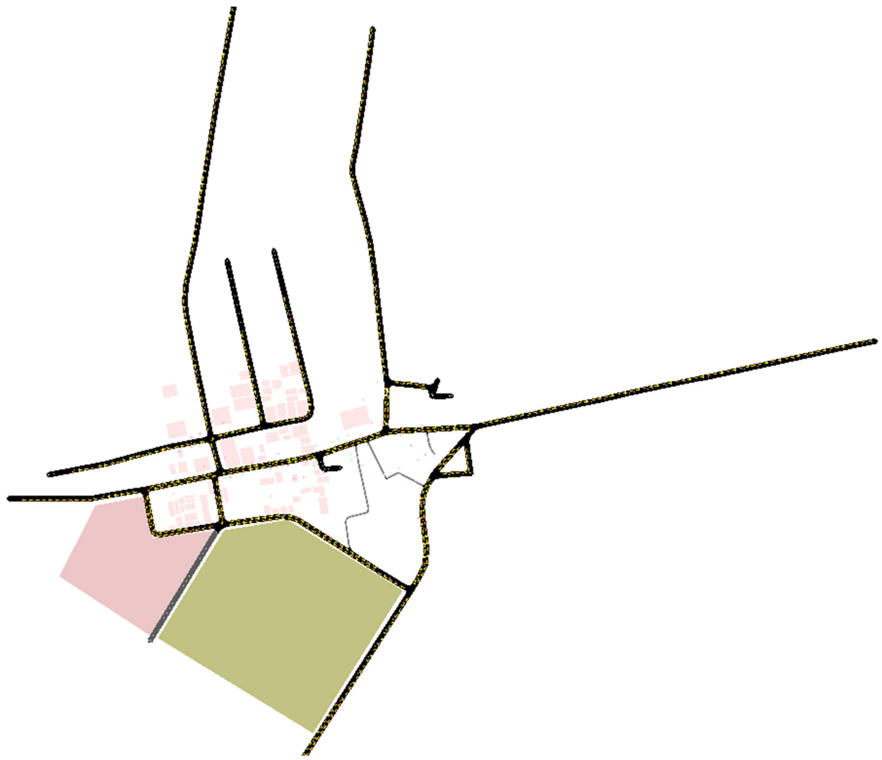

Figure 3 Sample Selected data in SUMO

7) A python-based library called TRACI was used to control the simulation in SUMO by establishing a connection to necessary libraries which interface reinforcement learning techniques.

The following simulation parameters were set before simulation.

Table 1. Experimental parameters used in simulation

Parameter	**Value**
Selected area	New Delhi, India
Node average speed	40-80 km/h
Number of Vehicles	20 – 100
Range of transmission	200 m
Size of Packet	256 bytes
Traffic Type	BER (Beacon Error Rate)
Time for Sinulation	200 s

The following traffics scenarios were considered for simulation

1) Two -lane traffic
2) Four-lane highway
3) Eight-lane Expressway

The number of vehicles passing per scenario is listed in table 2.

Table 2. Number of vehicles

Scenario	**Number of vehicles**
Two-lane national highway	507
Four-lane national highway	1183
Eight-lane expressway	2469

The following approaches are used for simulation:

1) 10Hz: Represents usual transmission of BSMs. Doesn't deploy mechanism for congestion control.

2) RTPC: Adjusts channel congestion via Random Transmission Power Control (RTPC). A vehicle transmitting at a constant power and rate produces channel congestion that matches these parameters.

3) QBCC: Deploys proposed algorithm for congestion control.

5. Results

Using the above approaches, the number of packets sent are represented in figure 4.

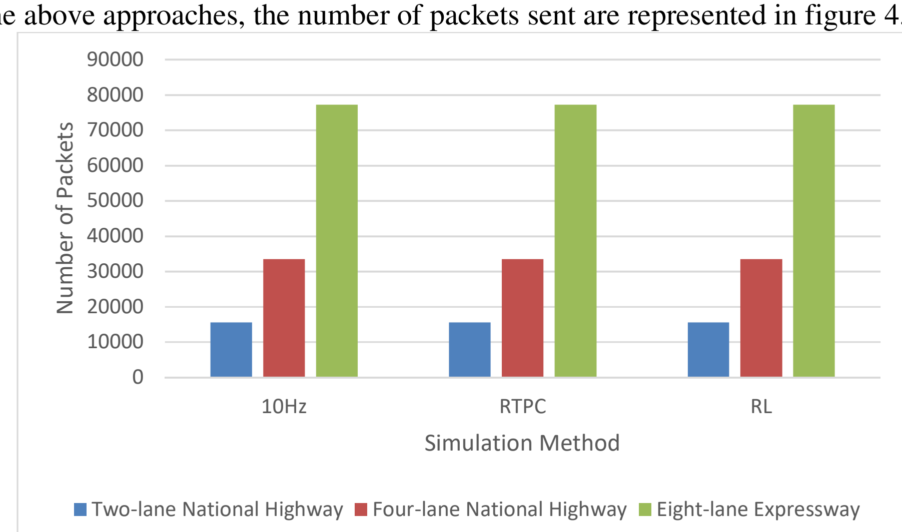

Figure 4 Comparison of total sent packets for different approaches

Similarly, the total number of lost packets are represented in figure 5.

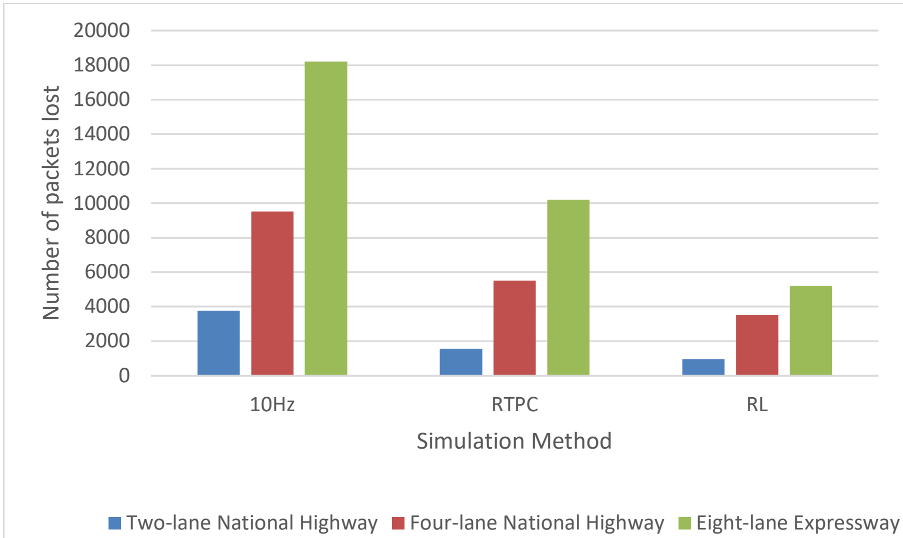

Figure 5. Comparison of total number of packets lost using different approaches

Accordingly, Beacon Error rate (BER) is calculated for each method and comparison is represented in figure 6.

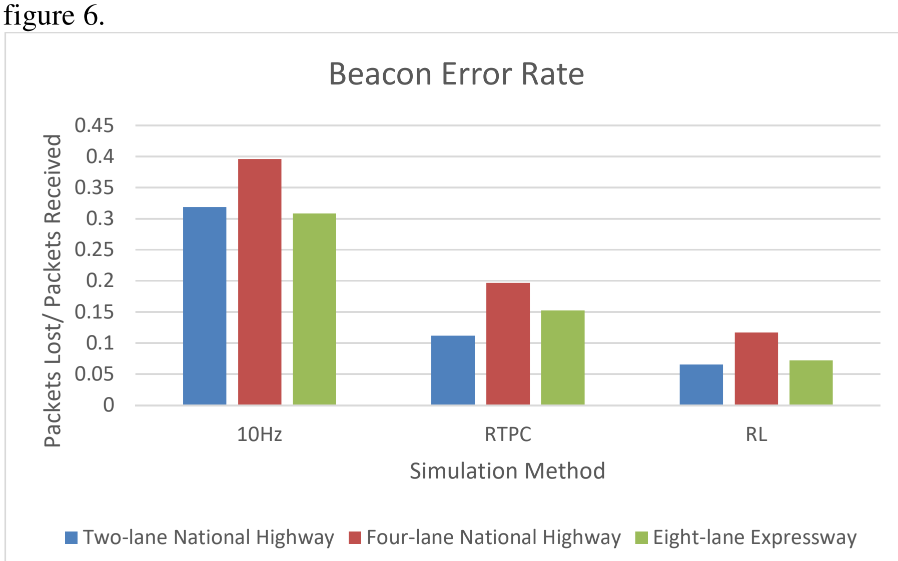

Figure 6. Beacon Error Rate for different methods

6.CONCLUSION

Controlling V2V communication congestion is one of the biggest issues facing car safety. An inventive method for teaching cars to attain the best gearbox specifications for delivering safety warnings is Reinforcement Learning (RL). In this research, we Q Learning based framework for controlling vehicular congestion and evaluate the system using dynamic traffic flow models. The findings show that, with the appropriate reward function designed, reinforcement learning is a viable method for controlling vehicular congestion. The Beacon Error Rate (BER) is minimum using Q learning method in comparison to other methods.

In future, we can focus on congestion control using Inter Packet Delay (IPD) optimization using reinforcement learning. We can extend the work on Vehicle-to-Pedestrian (V2P) communication since least amount of research work is done on the context.

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