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Intelligent Traffic Management: SARSA Learning Approach for Congestion Control in VANETs

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Abstract: — VANETs (Vehicular Ad-hoc Networks) are an intelligent type of vehicle network that is utilized for successful vehicular communication. The primary goal of VANETs is to send basic safety messages (BSMs) to On-Board Units (OBUs) inside vehicles, allowing for improved network traffic monitoring. Vehicles can interact in a complicated, dynamically changing environment to ensure consistent delivery. The limited channel capacity and dynamic nature of the network might cause channel congestion in VANETs, posing the most significant issue in the research. We presented a SARSA-based framework for intelligently determining optimum transmission settings while adhering to recent channel circumstances. The necessary implementation results have been demonstrated, demonstrating that RL approaches provide an efficient solution for adaptive congestion control.

Keywords: Channel Congestion control, VANET, SARSA learning, BSMs, OBUs

1. Introduction

Ensuring safety is a significant issue in vehicular road traffic situations. In 2020, almost 38,680 individuals died in accidents, marking one of the highest casualty rates since 2007. To enhance vehicle safety and raise awareness, it is crucial to utilize wireless technology such as radio, cameras, and lights, in addition to addressing drivers' attitudes and behaviors. Vehicular ad-hoc network (VANET) is considered important by several entities such as government, automobile manufacturers, and academics as a key component of the intelligent transport system (ITS) to enhance safety among cars. Vehicular communication can be done by Roadside units (RSUs) or Onboard units (OBUs) under separate paradigms. Vehicles can interchange safety related messages between themselves by a connected network which include warning messages for sudden lane change, collision avoidance and warning for sudden braking etc. The BSM (Basic Safety Messages) [12] (or BAMs) (also known as Cooperative Awareness Messages [13] (CAMs) can be distributed with freshness and availability, both of which are critical for the operation of various applications designed to enhance vehicle safety. Fig. 1 represents basic components of VANET.

Congestion increases due to increase in vehicle density and reduces transmission capability. Transmission parameters are of two types: 1) transmission power and 2) message rate. To minimize congestion most researchers have targeted optimization of the parameters. A major drawback of the techniques is to increase inter packet delay (IPD) [17]. A study[18] represents that optimization among parameters is a more difficult issue to address. High mobility of nodes 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 i.e. each node can take “right” decision to decide which safety messages to work upon.

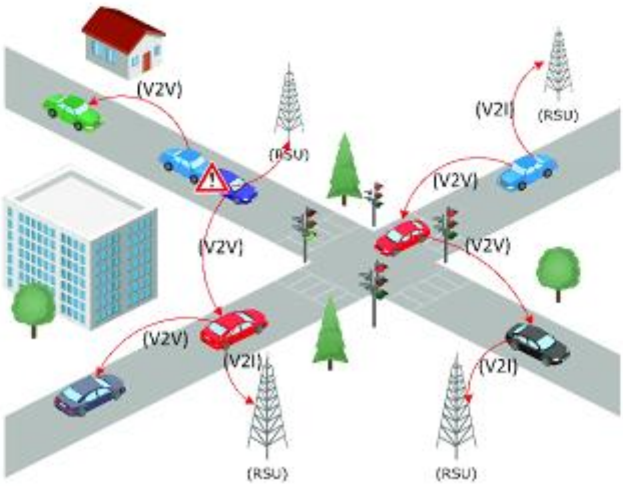

Fig1. Basic components of VANET

We use Markov Decision Process (MDP) for selecting beacon rate where Reinforcement learning uses each vehicle as agent and other communicating vehicles as environment. A SARSA-learning method is applied for training the vehicles for making appropriate choices. SARSA-learning uses the observations from the dynamic environment, like channel busy ratio and dynamic vehicle density. The focus of the research work are listed below:

• A framework is proposed for congestion control using reinforcement learning.

• We use data taken from traffic environment to apply on SARSA-learning algorithm and calculate CBR for efficiency.

• CBR and beacon collectively define reward function for maintaining channel load.

• Results of implementation represent that SARSA-learning methodology can maintain balanced traffic under diversified conditions.

1.1 Literature Survey

Channel Congestion control in VANET

VANETs have evolved quickly for supporting diversified traffic, supporting a wide range of applications, especially security-related applications such as advance notifications for collisions, violation messages for traffic-signals, applications including systems for providing weather information, nearest/ cheapest restaurant location etc. Various safety specific applications depend on event-driven 'alert' notifications, as well as regular BSMs containing critical data, like speed, positioning and direction of the nearest vehicles participating in traffic. Due to the limited channel capacity, and the fact that BSMs need to be delivered reliably (in order to maintain an appropriate level of awareness), reliable BSM delivery has proven to be a challenge for VANETs. Hence, multiple research work has been conducted emphasizing congestion control algorithms for BSMs in recent years.

Common parameters used to control channel congestion are message transmission rate (MTR) and power (or a mix of both) [20-22]. Apart from them parameters like carrier sense threshold and data rate are also utilized to control congestion. [22-23] Machine learning helps to improve performance in a variety of tasks in different industries, including finance, healthcare, etc. Mohammed et al. [24] focused on machine Learning based congestion control techniques are utilized for providing solution of different challenges in VANets [25].

Machine Learning (ML) solutions for VANets have been applied in various contexts, including misbehavior detection (MDA) [27], multi-hop broadcast protocols (MUPs) [28], DDoS attack detection (DDoS) [29] and delay minimization routing (LMR) [30]. In recent years, several papers are suggested Machine Learning-based solutions for congestion control and load balancing of heavily used VANET communications. Taherkhani and Pierre proposed Locally Located and Centralized ML-CC as a solution to the congestion at the intersections. The ML-CC strategy was based on K-means clustering.

According to this model, Roadside Traffic Units (RSU's) are installed at intersections to collect all the traffic transmitted by different nodes within their area of coverage. H. Ye et. al. used deep-reinforcement learning and solved problem of resource allocations in vehicular communications, using unicast as well as broadcast methods. Primarily it is based on resource allocation and the appropriate message selection for onward transmission. E. Ghadimi et.al used reinforcement learning for controlling power utilization in vehicles and rate adaption by radio access network downlink for cellular networks.

J. Aznar-Poveda et. Al. proposed an optimized beacon-rate selection using function approximation with different policies.

J. Aznar-Poveda et. Al. proposed a multi-spatial Reinforcement Learning based dynamically changing channel assignment on MAC layer. Here nodes share their individual reward among other nodes adjustment of their channel selection decisions.

C. Choe et.al. and A. Pressas et.al. have proposed developed protocols for MAC for efficient use of channel sharing in wireless communication. Due to unreasonable number of research activities regarding RL are conducted on vehicular communications, the current work presents a specific RL methodology for congestion control in VANET.

The overall comparative study of the related works are summarized in table 1.

Table 1: Related work Channel Congestion control in VANET

Author(s)	**Main Contribution**	**Keywords**	**Key Focus**
Navdeti et al. [21]	propose Distributed α-Fair Transmit Power Adaptation Based Congestion Control in Vehicular Ad-hoc Network to discover and reduce traffic congestion.	VANET, DFAV, DV-CAST, and UV-CAST	Used transmit power control and optimum node selection for cooperative VANET in the framework of utility function optimization.
Kumar and Kim [22]	Suggested a novel MAC protocol for VANET known as Bitmap-based Hybrid Medium Access Control (BH-MAC).	VANET, MAC, TDMA, Hybrid MAC	The results reveal that BH-MAC decreases access collisions, enables faster channel access, and boosts throughput when compared to VeMA
Math et al. [23]	Presented a novel decentralised combined message-rate and data-rate congestion control (MD-DCC) strategy	Reliability, Safety, Resource management, Channel capacity, Convergence, Conferences, ETSI	Examined numerous implementation aspects, including the selection of MD-DCC settings and their relationship to application needs.
Mohammed et al. [24]	Takes a more practical approach, outlining the basics of machine learning algorithms and describing the areas of application for each algorithm	Machine learning, machine learning algorithms	Using easy practical examples to exemplify each method and show how different challenges linked to these algorithms.
Chaoji et al. [25]	Utilizing a hands-on approach to introduce the audience to machine learning.	Computing methodologies, machine learning	Provides a broad overview and examines some essential topics in machine learning.

Liang et al. [26]	Highlighted the unique characteristics of high mobility vehicular networks and proposed the use of machine learning to overcome associated difficulties.	Machine learning, vehicular networks, high mobility, Internet of intelligent vehicles	Introduced machine learning ideas and discussed how it can be used to optimize vehicular network performance by understanding its dynamics.
Grover et al. [27]	Described a machine learning strategy for classifying numerous misbehaviours in VANET by utilising tangible and behavioural aspects of each node.	VANET, WEKA and received signal strength (RSS)	Implemented several forms of misbehaviours in VANET by altering with information contained in the propagated packet.
Slavik and Mahgoub [28]	Proposed employing the distance-to-mean approach to make the VANET applications easier.	Protocols, Slabs, Optimization, Mathematical model, Rician channels, Fading, Bandwidth	VANETs have a wide variety of these characteristics, hence protocols built to serve the applications.
Alrehan and Alhaidari [29]	Focused on studying the main attacks along with DDoS attack on VANET system.	VANET, DDoS, Machine learning, SDVN, Security	Distributed Denial of Service (DDoS) attacks are one of the most serious risks to VANET's availability.
Tang et al. [30]	Proposed a centralized routing method with mobility prediction for VANET.	Vehicular ad hoc network (VANET), routing, software-defined network (SDN), machine learning	Using an advanced artificial neural network technique, the SDN controller can accurately forecast mobility.

2. Objectives

The objective of the current work is to create a congestion control mechanism for Vehicular Ad hoc Networks (VANETs) based on reinforcement leraning strategy to effectively regulate network congestion while ensuring fairness in data transmission rates. VANETs are frequently congested due to high vehicle mobility and dynamic network circumstances.

3. Methods

Since wireless channel has a limited bandwidth, congestion control is the biggest challenge in the safety communication. It's basically aims to reduce the channel traffic, i.e., to determine the safety parameters for the communication path. In rapidly changing mobile environments, the nodes are required to decide the necessary action for controlling their channel load in multiple situations. For instance, in a situation where the vehicle density is low, the lower the density, the lower the channel load. The best action to control this channel load must raise the rate of transmission for ensuring a higher BCM delivery rate. In a situation where the density is high, it is necessary to select the transmission rate accordingly. Congestion control provides decision regarding multiple factors like the vehicle density, CBR, BER, IPD etc.

The above parameters can be extracted or estimated from the normal safety messages that the node receives from other nodes. According to the problem definition each node decides on its transmission parameters(s) according to current traffic flow and channel state.The future property depends on present and hence independent on past, defined as Markov property, stated below:

$$P\,[St + 1|St] = P\,[St + 1|S1, \dots, St] \quad (1)$$

The fig. 1 represents RL in vehicular communication.

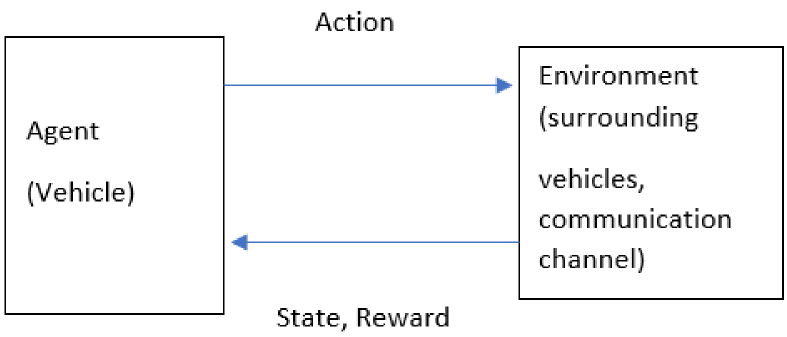

Fig. 1. Reinforcement Learning cycle in Vehicular Communication.

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 (Rt+1) and changes into state (R+1). The vehicle aims to optimize total reward (Gt).

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

$$Gt = (R_{t+1}) + (\gamma R_{t+2}) + (\gamma\ 2R_{t+3}) + \dots = \sum_{k=0}^{\infty}(\gamma R_{t+k+1}) \quad (2)$$

where $0 \leqslant \gamma \leqslant 1$. When γ is close 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 qπ(s, a) determines the action value for a given state and policy. To increase efficiency, minimize qπ(s, a) and describe the state-action value function as:

$$q_*(s,a)=\max\,[q_\pi(s,a)] \quad (3)$$

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

$$\Pi_*(a\,|s\,)=\begin{cases}1 & if\ a = argmax\ q*(s,a)\\ 0 & otherwise\end{cases} \quad (4)$$

a. Components of MDPs

The primary objective of the work is to conceptualize the congestion control challenge as a congestion management problem (MDP) and to demonstrate methodology to resolve the same by reinforcement learning methods. Action and state space for Markov Decision Process are discrete and finite, hence beacon rate is to be balanced for ensuring congestion control in channel. 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 SARSA learning framework of Vehicular communication are given below:

A) 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.

B) 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, $a \in N$, $1 \leqslant a \leqslant 10$.

C) State: Represents the situation of the environment. It can be affected by the actions taken by agent. Due to action a new state is formed. In this work, the space includes the CBR and vehicle density, where CBR lies in the interval [0,1], and V D is a whole number in the interval [1, 50]. Here vehicle density assumes the number of vehicles in 100 m radius. In a case study, 10 CBR values for 10 beacon rates are taken per vehicle. Vehicle density varies with neighbor's BSM, so the entire state space will be made up of 500 separate states. In every state, we can select out of 10 separate beacon rates and determine the current vehicle density. After obtaining the CBR value, we can decide the new state.

D) Reward function: An agent learns based on the reward provided by its environment after it performs an action. The reward associated with each action is determined by the reward function. The reward function can be designed in a way that meets the learning goals. Our recommended methodology is to keep the CBR under a defined η while sending required number of SBMs.

Accordingly, the reward function is as defined:

$$r(CBR, BR) = BR * CBR * \sigma(\eta - CBR) \quad (5)$$

Here σ = signum function shifted by target value η. If CBR > η then a negative reward is earned, which can speed up the learning process [39]. In case of low beacon rate the reward will be lower. In this work, η = 0.6 is taken assumed as the target channel load. According to separate scenarios η can be updated or a different reward function should be utilized.

b. SARSA-learning technique

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

Update statements for SARSA learning technique can be defined as follows:

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha(r(s_t, a_t) + \gamma\, Q(s_{t+1}, a_{t+1}) - Q(s, a_t)) \quad (6)$$

Here, SARSA updation depends on the current action, current state and reward obtained, next state and next action, abbreviated as **State Action Reward State Action** i.e. (s, a, r, s', a').

The SARSA algorithm ∊greedy policy for updating in Q-table as per equation 6.

Algorithm #1 SARSA-learning Based Adaptive Congestion Control (SBACC)

1. Assume s as initial state.
2. Use epsilon-greedy policy based on current Q values to select initial action.
3. Find next state s' for action a and reward r.
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 SARSA update rule:

$$Q(s, a) = Q(s, a) + alpha * (r + gamma * Q(s', a') – Q(s, a))$$

The congestion control implemented by SARSA is implemented in 2 phases. The first phase is the implementation of the Q-Table with optimal policies for each state. The Q-Table is generated using the observation data derived from a simulation. The second phase is to apply the Q-Table to a dynamic traffic environment in VANET.

50 numbers of traffic models were analyzed with variable vehicle densities, ranging from 1 to 50 cars per 100 metres, to build the Q-Table for each state. To obtain the analysis data for every action in each stage, we ran simulations with our proposed action space for each traffic model, using a beacon rate ranging from 1 to 10. The SARSA-Learning method was then applied to the analysis data, producing a Q-Table for every vehicle density, and combining them for the entire state space.

4. Implementation & Results

Implementation of SBACC used a framework named "Vehicles in Network Simulation" (Veins) used the following configuration parameters as given in Ta-ble I. We'll create a 4 km wide, rectangular highway (1 km wide on each side) with 500 and 1000 vehicles driving continuously around the rectangle at random speeds (60, 120, and 140 km/h respectively) to obtain dynamic traffic flow at random density (1 to 50 vehicles in 100m radius). The vehicle only needs to call the Q-Table to find for the optimal beacon rate because it already knows the best policy for each state based on the current beacon rate (SARSA-learning).

Veins used Beacon rate between range [1,10] BSM per second. The transmis-sion power used at standard value of 20 mW. The average size of BSM was 512 B. The used data rate was 6 Mbps. The minimum power level used was -110 dBM with noise floor -98 dBm. Vehicle density ranges between [1, 100] vehicles per 100m distance. Assumed 4 lanes in highway per 4 kms. The average simulation time taken was 100s.

The algorithm used by each vehicle to calculate the beacon rate in OMNeT++ as given below:

Algorithm #2 SBACC Policy Application using OMNeT++

1: R = 5
2: For density = 1 : 50 then
3: if density == D then
4: For BR = 1 to 10 do
5: if CBR ≥ C
6: mValue = Maximum row value for BR and D
7: R = BR for mValue
8: break
9: Send beacon with R

The algorithm used the following abbreviations:

C= Current CBR
D= Current Vehicle Density
R= Best Rate
BR= Beacon Rate

A car finds the vehicle density after determining the current CBR. It then sends the BSM along with a search for the best beacon rate using the Q-Table. Owing to space limitations, only a subset of the values are displayed in Table II rather than the full Q-Table. The CBR and vehicle density in each row indicate the environ-mental status. The ideal course of action, or optimal policy, is represented by the beacon rate with the highest value. The methods for comparing the performance to the dynamic traffic model are listed below.

For all approaches, 20 mW fixed transmission power was used. The four ap-proaches are:

a) 10 Hz
b) 5 Hz
c) Random Rate Control
d) SBACC

In the current work, average CBR is used to measure the total channel load. 10 Hz always has the largest average CBR. 5 Hz average CBR is below 10 Hz. Ran-domized approach yields the smallest average CBR, but obtains the lowest num-ber of BSMs.The method is represented diagrammatically in fig.2.

According to individual vehicle density, SBACC's beacon rates range from one to ten, and in both scenarios, the average CBR continuously stays just around 0.5—the cutoff point that we employ in the reward function. In comparison to the random beacon rate strategy, the SBACC technique has received more BSMs (5677095 and 9949960, with 500 and 1000 cars, respectively), indicating that vehicle awareness is still strong.

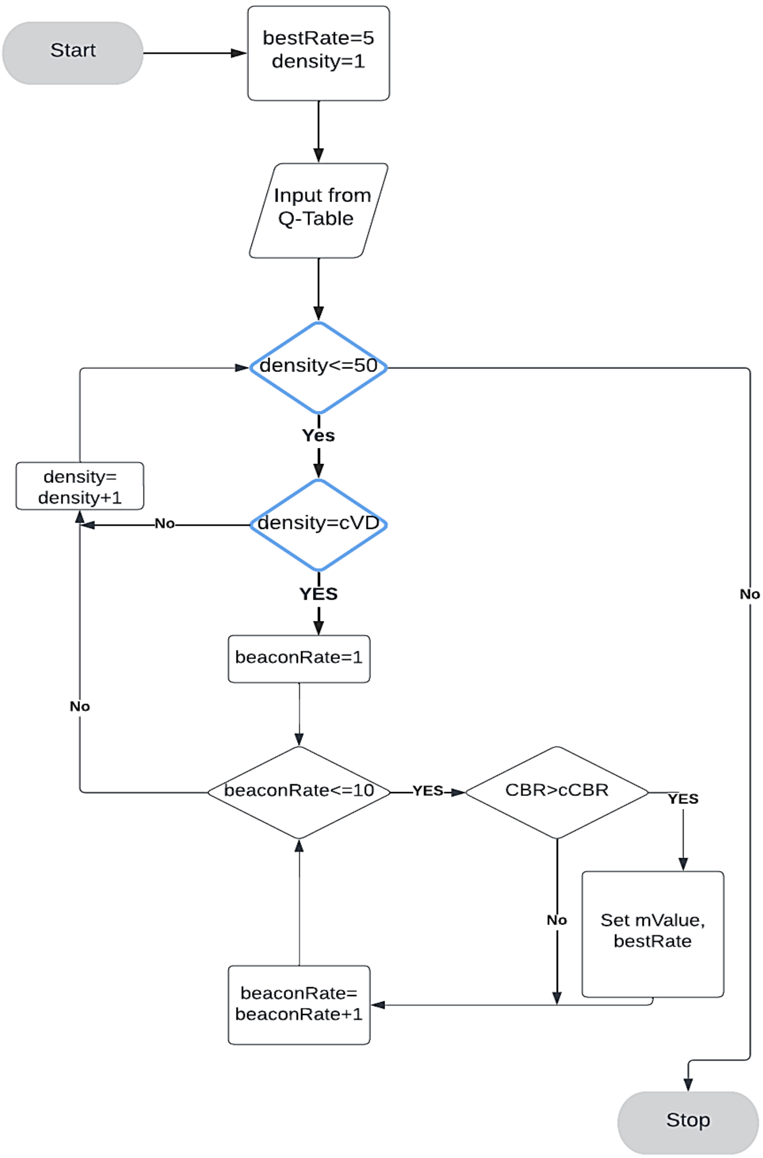

Fig. 2 SBACC Policy Step-by-Step Evaluation

Table 2. Sample data in SARSA-Table

Vehicle Density	**CBR**	**Beacon Rate**				
		No of BSM 1	**No of BSM 3**	**No of BSM 5**	**No of BSM 7**	**No of BSM 10**
1	0.2703	70.1	28.1	44.4	32.1	46.4
5	0.72623	78.1	81.2	87.3	101.2	41.2
15	0.9246	57.1	7.3	-2.2	-4.2	-23.1
50	0.93	47.1	-24.4	-46.1	-87.3	-121.3

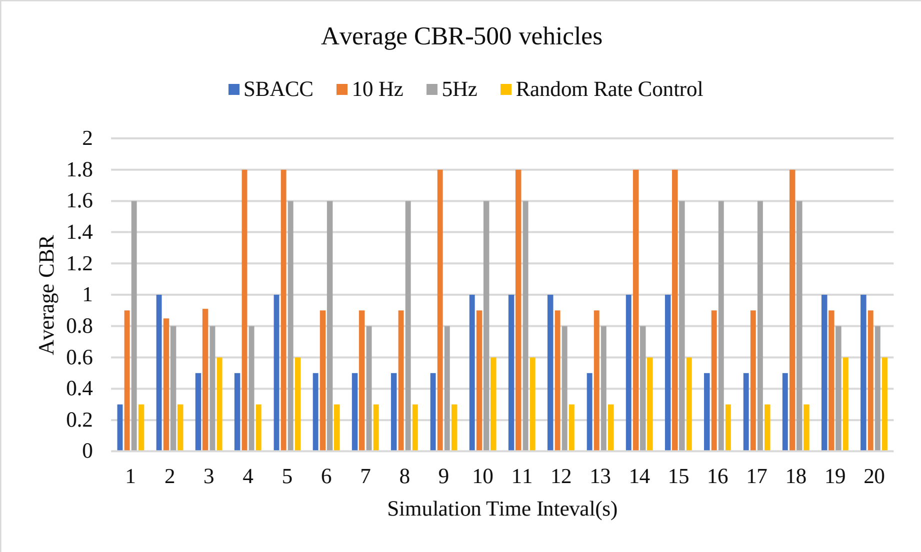

Fig. 3 Average CBR for multiple algorithms with number of vehicles 500

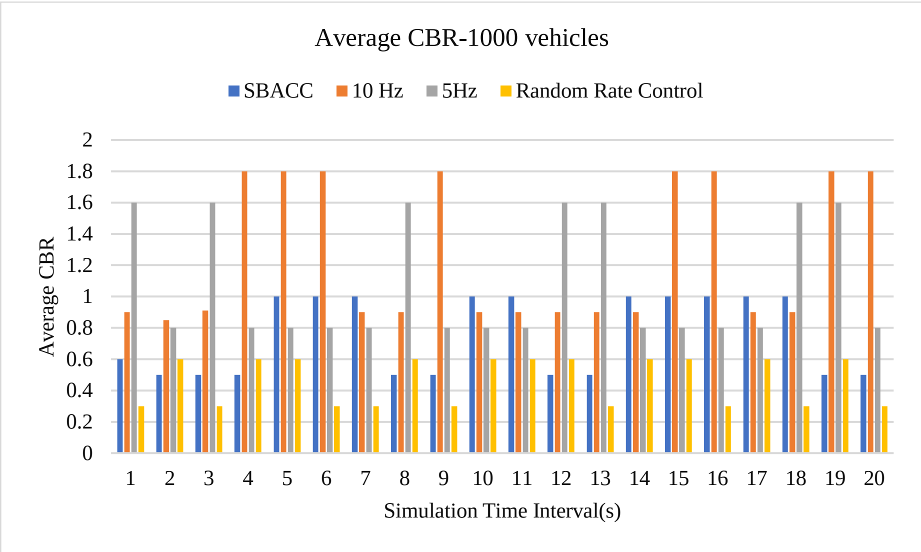

Fig. 4 Average CBR for multiple algorithms with number of vehicles 1000

5. Discussion

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 design the components of Markov Decision Process model, present a SARSA Learning based framework for controlling vehicular congestion and evaluate the system using changing traffic flow models. The findings show that, with the appropriate reward function designed, SARSA learning is a viable method for controlling vehicular congestion.

Suggestions for future work:

Multiple metrices like IPR, BED can be used to enhance congestion control. Also , deep learning techniques can be integrated with traditional machine learning techniques to improve congestion control.

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