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Optimal Data Rate and Power Estimation for Channel Congestion Control in V2V Communication

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Abstract: The prospects for vehicle mobility will focus on complete automation. Connected systems is the technology which is booming, making a common man's life simple, be it in home environment, industries, public spaces or in transportation. The technology which is currently gaining pace in research is on Vehicle-to-Vehicle (V2V) Technology. This involves a network of motor vehicles that continuously access information from or sharing information to the peer vehicles which are driving along. This data exchange can help drivers be alerted to such as possibility of accidents, obstacle detection and presence of traffic gridlocks during travel. Researchers are facing certain hurdles while developing optimum algorithms related to sub-domains of V2V. Amidst these challenges, one is on adjusting the channel capacity. When data is sent, it must be transmitted in a way that no data gets corrupted or lost. Since the environment of vehicle movement is rapidly dynamic, there involves a lot of decision making at every small instances of time. Hence, with the help of previously observed scenarios, performance parameters and Reinforcement Learning (RL) concepts, the decision making could be manageable. The project focuses on managing data rate and transmission power value for every message sent for various scenarios that aids in channel being adequately used. The vehicle traffic is simulated running on an intersection scenario with DSRC Communication. Certain performance metrics such as Packet Delivery Ratio, Channel Busy Ratio is considered to verify the efficiency of the RL model and compared with existing one.
Keywords: V2V Communication, Channel, DSRC, Reinforcement Learning, Vehicle Intersections, LTEV2VSim

I. INTRODUCTION

Vehicle-to-vehicle communication technology, commonly referred to as V2V, is a cutting-edge technology that enables the exchange of vehicle data between two vehicles. Using a wireless communication protocol similar to Wi-Fi, V2V communication allows motor vehicles to access information about the speed and location of other V2V-enabled vehicles surrounding them. This data is then used to alert drivers of potential hazards, helping to reduce accidents and traffic congestion. V2V can detect dangerous traffic and road conditions, terrain issues, and weather threats within a range of 300 meters. The technology has the potential to make driving a safer and more predictable activity for everyone on the road. The benefits of having more connected vehicles due to V2V includes providing businesses with access to comprehensive information that can help them improve customer service, increase efficiency and productivity, promote safer habits for workers and drivers, and manage a reliable return on assets and vehicles. The appropriate technology can extend the functionality of telematics by assisting drivers in improving their routes, enabling them to cover fewer miles and serve more customers during a given shift, thereby enhancing both customer satisfaction and profitability. V2V systems offer intelligent features that improve driver awareness through traffic alerts, informing them of congestion, obstacles, lane changes, traffic merging, and railway crossing alerts.

A number of Institute of Electrical and Electronics Engineers (IEEE) and Society of Automotive Engineers (SAE) standards for connected vehicle technologies for safety and crash avoidance are the foundation for the DSRC-based V2V system. These safety applications rely on vehicle-to-vehicle (V2V) safety communication, which disseminates vehicle status data via Basic Safety Messages (BSMs). The BSMs contain essential state data such trip history, speed, acceleration, brake status, and location via the Global Navigation Satellite System (GNSS). Specifically, these V2V systems make use of the SAE J2945/1 standard, which is derived from many IEEE and SAE standards.

Channel contention and increasing interference cause congestion on the channel in high-traffic environments with plenty of automobiles (transmitters).

There are several basic limitations on channel bandwidth, particularly as a wireless network expands. The IEEE 802.11p standard uses Carrier-Sense Multiple Access with Collision Avoidance (CSMA/CA) as the medium access protocol as the standard method of handling interference. When a vehicle or node in CSMA/CA has a packet to send, it first listens to the channel. The packet is transmitted if the channel is judged to be vacant or idle. If not, the node transmits the packet after waiting a random back-off period. Although this approach lessens the likelihood of packet collisions, it does not completely prevent them.

The performance of safety applications may therefore needlessly suffer in big and dense V2V networks if all vehicles send their BSMs at the same high transmission rate and transmit power. High packet losses as a result impair V2V situational awareness and make it challenging to anticipate a vehicle's movement or quickly identify an impending crash. Therefore, reducing channel congestion has been extensively researched to solve the scalability issue and strengthen safety applications [1]. Section II talks on the works done with regards to optimization of parameters. Section III involves the complete methodology which involves building and training an RL model. While Section IV showcases the results while comparing with another technique, Section V briefly discusses on the inferences and future scope on improving the proposed technique.

II. LITERATURE REVIEW

The authors [2] evaluated the behavior of connected autonomous vehicles (CAVs) at many nearby crossings. Here, a bilevel decentralized coordination system for CAVs at several nearby multilane signal-free crossings without signals has been described. Each CAV iteratively calculated the energy-optimal arrival time at each intersection along its path in the higher level planning, making sure that both rear-end and lateral safety were maintained. For every CAV with interior-point constraints, we establish an optimal control problem in low-level planning. The optimal control input in terms of energy is obtained by solving this problem, given the time obtained from the upper-level problem. Each CAV that implements a lane-changing zone looks into the viability of a lane-changing move and chooses the best lane to occupy in order to increase traffic throughput. The optimal control problem with interior-point restrictions has an analytical solution that may be applied in real time, along with a recursive framework for upper level planning and supporting equations. Furthermore, a bilevel framework is introduced to ensure safety for tracking the positions of CAVs in the presence of a bounded steady-state error. In comparison to the baseline scenario, the suggested framework showed improvements in travel time, reduced fuel usage, and reduced traffic delays at varying traffic loads.

Maintaining channel load is key to ensuring the appropriate operation of safety applications as well as driver-assistance systems. As the number of vehicles increases, so do their communication messages. Therefore, channel congestion may arise, negatively impacting channel performance. Through suitable adjustment of the data rate, this problem would be mitigated. However, this usually involves using different modulation schemes, which can jeopardize the robustness of the solution due to unfavorable channel conditions. The paper [3] discusses on employing an analytical model which balances the data rate and transmission power in a non-cooperative scheme. A Deep Neural Network (DNN) is trained to precisely optimize both parameters for each vehicle without using additional information from neighbors, and without requiring any additional infrastructure to be deployed on the road. The results obtained revealed that it not only alleviated congestion, leaving a certain fraction of the channel available for emergency-related messages, but also provided enough transmission power to fulfill the application layer requirements at a given coverage distance. This was thoroughly tested and evaluated in three realistic scenarios and under different channel conditions, demonstrating its robustness and excellent performance.

A proposed broadcast-rate optimization technique for V2V communications was based on theoretical interference analysis [4]. Due to traffic congestion and street crossings, cars near intersections typically encounter more interference than vehicles operating in other regions. Moreover, a high broadcast rate makes vehicle interference worse. The likelihood of the automobiles transmitting packets is increased. The metrics that measure the performance of V2V broadcast communications at an intersection based on a stochastic geometry approach are investigated in order to quantify the interference impact at an intersection and the relationship between the interference and broadcast rate. By obtaining tractable (approximate) formulations of the performance metrics, the broadcast rate can be optimized in a reasonable amount of computational time, minimizing intersection interference and optimizing the overall performance of V2V broadcast communication.

The subject of resource block (RB) sharing is the primary emphasis of this study [5]. Considering that several V2V links can share a single resource block (RB) and that each link can occupy a maximum of one RB. Through function mapping, a factor graph model that corresponds to the RB allocation problem is proposed in this paper. As a result, analyzing the factor graph model's message update and belief inference problems is analogous to understanding the RB allocation problem. A Belief Propagation based on Real-time Update of Messages (BPRUM) algorithm is developed, wherein each node's message is computed using the most recent messages from other nodes, as opposed to the messages computed during the previous iteration. Second, using the Lagrange dual decomposition, a power control strategy under the maximum power limit is proposed when the RB allocation is finished. Additionally, the suggested power control technique maximizes the system's overall throughput. The results of the simulation demonstrated that the resource allocation and power control method may significantly increase the V2V communications network's throughput and spectrum usage.

When considering a scenario of vehicles approaching an intersection, the message channel is an important measurement procedure. This analysis work [6] starts with a practical path loss model considering intersection spatial structure is proposed based on the intuitive observation of channel energy in the previous work. This model is based on the classic two-ray structure, which can accurately reflect the extra increase of path loss caused by obstruction. At the same time, the selection of breakpoints considers the spatial position of obstacles. Therefore, the proposed method can be applied to the path loss modeling of various conventional intersection environments. In addition, further investigation of the spatial characteristics of intersection channels is done too. The time-varying change of overall channel spatial stationarity is quantified and analyzed, and on the other hand, the energy-angle distribution of MPCs is presented. The MPC (Model Predictive Control)-level analysis explains the source of the inherent influence of obstruction on channel energy, delay, and spatial characteristics. Finally, this article analyzes the energy distribution of specular components (SCs) and dense MPCs (DMCs).

The J3161/1 standard is based on V2V technology which uses cellular V2X transmissions. Here in the standard, there is no mention on the control on the data rate, only transmitted power control was proposed. The authors [7] have given a proposed solution to how the data rate is controlled which would be dual-control feature as well as eliminate the delay problem, that can decrease the probability of vehicle accidents. CBR and ITT parameters are taken into Deep Deterministic Policy Gradient (DDPG) to learn the parameter α that would iteratively improve and hence obtain rewards. The Packet Inter-reception time shows better results with Tx-Rx distance, when compared with DSRC standard considerations.

Distributed Congestion Control is gradually evolving with slight changes in order to support various scenarios. The study [8] demonstrates a new DRL model called range-adaptive distribute power control (Ra-DPC) with Monte Carlo policy gradient. The C-V2X communication interface is made of subchannels, each subchannel with a subframe that would be allocated to a VUE. This is a resource block for transmitting CAM, which can use multiple subchannels depending on the message characteristics. Instead of CBR, the parameter chosen is PDR since it is more reliable. The problem focused here is to adaptively monitor the power control in order to reduce interference from the surrounding VUE’s. The power is set to vary between the limits. The algorithm was compared with another SBPA model and was found to have better average PDR for wide range of testing episodes.

V2V technology with a backend of 5G Communication needs to accomplish key performance indicators (KPIs). They are user experience rate, connection number density and end-to-end delay. For this to occur, the design factors involved are high spectrum and energy efficiency. This work [9] considers mode selection and power adaptation based on V2V Communication in 5G networks. Joint mode selection and power adaptation scheme is involved for maximizing the total capacities. A decentralized scheme is also introduced to make decisions autonomously without BS interference in decision making. The RL framework is developed for the joint mode selection and power adaptation called DDQN, which introduces a feature wherein reward function manages the interference in order to improve the performance. The algorithm aims to improve reward with learning, improve sum throughput of V2V and V2I links and mode selection for different ratios of links.

The authors [10] formulated a new Multi-Objective Optimization (MOO) problem to represent the decision process in a complex wireless network with multiple V2V links sharing the same spectrum. The problem takes the impact of environment change into account, and aims to achieve the trade-offs between the optimization goals of different links, while ensuring the QoS of delay-sensitive messages. The proposed novel framework to solve the MOO problem was inspired from wireless sensor and mobile systems. The challenges caused by the imperfect CSI, non-linear form of the objective function, time-related constraints and mutually-conflicting objectives, are tackled in sequence. By this means, a MOO-based sequential transmission design algorithm for the V2V communication network was established. Extensive simulation experiments were conducted to investigate the performance of the proposed algorithm. The solution is shown to be able to effectively trade off the achievable performance of different V2V links, and adapt to the quality of available channel knowledge and QoS demands. Through the comparison with several representative baseline schemes, its efficiency is clearly demonstrated.

The paper [11] is on the transmit power parameter optimization for message communication with Cellular links. The parameter was traditionally modified using NP-hard problem-solving methods. With the help of DNN, there is a reduction in the complexity faced before. Three benchmark methods are considered and is compared with the proposed algorithm. The algorithm uses DNN for providing final transmit power, with the inputs of channel gain at the input layer side. The channel is based on CUE (Cellular User

Equipment) and VUE (Vehicle User Equipment) for V2V links. The algorithm not only achieved high sum-rate, but also achieved lesser time complexity. The sum-rate was observed for velocity, no. of V2V pairs, and maximum transmit power.
From the papers referred, the scenarios mentioned had highways or multiple lanes where vehicles travel in a single direction. Whereas, this work goes for testing out how the vehicles interact with neighboring at the intersection sites. Here, RL model is functioned to adjust data rate and power to send the messages while maintaining the channel usage.

III. METHODOLOGY

The vehicle transmission of messages between vehicles should be working in a flawless manner. Constant update of Basic Safety Messages (BSM) is necessary so that every vehicle is aware of the surroundings. For it to receive successfully, the parameters of message transmission should be optimal for every instant of vehicle state. Factors to look into the state of a vehicle are speed, orientation (2-dimensional), nearby vehicle density. A Reinforcement Learning could be a better choice over DNN, since it involves constant learning from the mistakes that it has done from the real time scenarios that the vehicle experiences. With the mathematical equations designed for providing the accurate parameter values, the vehicle will gradually work on the obtaining good rewards. A general Reinforcement model has these elements:

1) Environment – Physical world in which the agent operates
2) State – Current situation of the agent
3) Action – Agent's decision or configuration taken for the particular state
4) Reward – Feedback from the environment
5) Policy – Method to map agent's state to actions
6) Value – Future reward that an agent would receive by taking an action in a particular state.

For the data rate, [4] proposed an approximate analysis for three different cases: transmitter at intersection, transmitter at the start of the queue and transmitter at the end of the queue. In this project, the focus would be to consider the first case and also look into optimization formulas suggested for this.

The analysis of data rate is done using the following equations. These equations help in filtering out the data values among the unnecessary ones.

a) Interference Distributions

$$I_Q = \sum_{m=1}^{n_- + n_+} \delta_m h_m d_m^{-\alpha} \quad (1)$$

Here in Eq. 1, Q is one of the vehicles present in the queue of intersection, d_m is the distance between receiver and the m^{th} vehicle and h_m is the Independent and Identically Distributed exponential variables with a mean since Rayleigh fading is considered.

b) Probability of Successful Transmissions

$$p(r) = \mathcal{L}_{I_Q}(Tr^{\alpha}|d')\mathcal{L}_{I_R^X}(Tr^{\alpha})\mathcal{L}_{I_R^Y}(Tr^{\alpha}|d') \quad (2)$$

The probability is dependent on Laplace Transforms of Interference caused by Queuing Vehicles, running vehicles on both X and Y direction as in Eq. 2.

c) Mean no. of Successful Receivers

The Eq. 3 defines the number of vehicles to which the message is expected to be delivered safely.

$$\bar{M} = (1-\rho)\sum_{i=n_-}^{n_+} p(|d - il_v|) + (1-\rho_0).[\lambda_x \int_{\mathbb{R}} p(r)dr + \lambda_y \int_{\mathbb{R}} p(\sqrt{(d^2 + r^2)})dr \quad (3)$$

For power control, [5] has proposed a power allocation scheme called "Lagrange Dual Decomposition". The power control is normally a NP-hard problem and hence a dual iterative approach is implemented. Firstly, maximizing the sum rate of V2V links with approximating link rate expression log(1 + SINR) by log(SINR). Secondly, in order to avoid that a single user maximizes power during the maximization process, a penalty term P_m is taken.
Finally, to summarize the entire methodology, Fig. 2 shows the flowchart of the tasks performed in order to build and train a RL model for data rate and power that supports intersection scenarios.

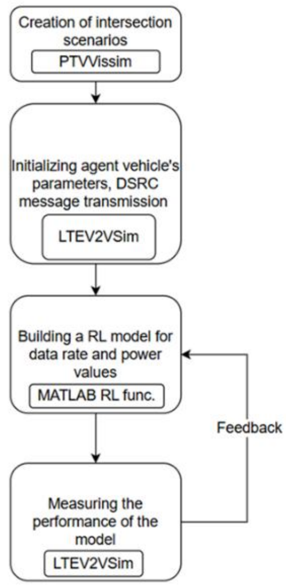


Fig. 1.Flowchart of the methodology

A. DSRC Standards

V2V safety communications are designed to exchange basic safety information among vehicles for driver assistance by supporting detection of imminent crash threats and alerting the driver. V2V communications use Dedicated Short Range Communications (DSRC) radios to transmit BSMs that include a subset of the available data frames and elements in SAE J2735. Onboard safety applications use the information about the Host Vehicle (HV) and Remote Vehicles (RVs) to detect potential crash threats and alert the driver. Messages can be used for additional purposes, but only the scenarios described herein were used to develop this Standard. For the purposes of the crash scenarios described herein, the HV and RV terminology is used to identify which vehicle is receiving and acting on BSMs (HV), and the set of vehicles from which BSMs are being received (RVs).

V2V communications can enable improved safety system effectiveness by complementing or providing an alternative to self-contained sensors such as RADAR, LiDAR, or camera systems. V2V communications provide the vehicle and driver with 360-degree awareness and can detect potential threats at a greater distance than other types of sensors, as well as detecting potential threats to some degree even under non-line-of-sight or low visibility conditions. This enables the driver to receive alerts earlier and have more time to take action to avoid crashes.

The V2V onboard equipment (OBE), which is the on-board vehicle-to-vehicle (V2V) safety communications system defined in this standard (hereafter referred to as the System), typically consists of multiple subsystem components, which may be discrete or integrated depending on the implementation.

DSRC Radio Subsystem – Transmits and receives BSMs. In this standard, a DSRC radio subsystem is assumed to be a single-channel-at-a-time device. The OBE can include one or more DSRC radio subsystems and still comply with this standard.

- Positioning Subsystem – The subsystem that includes a Global Navigation Satellite System (GNSS) receiver and provides vehicle position, heading, speed, and time information. This may augment and enhance positioning using additional information and components. Examples of these are speed data from the CAN bus, dead reckoning sensors and optical/camera-based systems.
- OBE Control Processor Electronic Control Unit (ECU) – Executes software that generates BSMs for transmission according to the requirements in this standard.
- Antennas – Support radio frequency (RF) links for the DSRC radio and GNSS receiver. A second diversity antenna for the DSRC Radio Subsystem is recommended to improve performance. GNSS and DSRC antennas may be integrated (dual band).

The BSM, which is defined in SAE J2735, is the message used for V2V safety communications in this standard. Each vehicle broadcasts BSMs to provide neighboring vehicles with trajectory and status information. With a sufficiently high population of DSRC equipped vehicles, the number of BSMs being transmitted can congest the channel, necessitating congestion control procedures.

The Connected Transportation System of Systems (SoS), consists of a collection of systems. Each system is comprised of various connected devices including vehicles (V), infrastructure (I), and other devices (D). Interactions between the devices within the system include Vehicle to Vehicle (V2V), Vehicle to Infrastructure (V2I), Vehicle to Device (V2D), and Device to Infrastructure (D2I). Additionally, systems that may be included in the SoS are developed to address more specific varieties of devices, as an example, with vehicles there are light vehicles (LV), heavy vehicles (HV), transit vehicles (TV), and safety vehicles (SV). Other devices such as Vulnerable Road Users (VRU) are examples that are not vehicles.

A DSRC-based system uses the protocols specified in IEEE Standard 802.11 and in the IEEE 1609 Wireless Access in Vehicular Environments (WAVE) series of standards. Applications that use the SAE J2735 data dictionary (messages) may use DSRC. Use of DSRC spectrum in the US is subject to FCC rules [49]. FCC rules specify seven 10MHz channels between 5.85 and 5.925 GHz: channels 172, 174, 176, 180, 178, 182, and 184. Channel 178 is designated the Control Channel (CCH); the others are Service Channels (SCHs). Per FCC rules Channel 172 is reserved for vehicle safety and 184 is reserved for public safety. Two 20-MHz channels are also available.

B. Q-Learning in RL

Q-learning is a model-free, value-based, off-policy algorithm that will find the best series of actions based on the agent's current state. The “Q” stands for quality. Quality represents how valuable the action is in maximizing future rewards.

The model-based algorithms use transition and reward functions to estimate the optimal policy and create the model. In contrast, model-free algorithms learn the consequences of their actions through the experience without transition and reward function. The value-based method trains the value function to learn which state is more valuable and take an action. On the other hand, policy-based methods train the policy directly to learn which action to take in a given state.

1) Key Terminologies in Q-learning:

Before we jump into how Q-learning works, we need to learn a few useful terminologies to understand Q-learning's fundamentals.

- States(s): the current position of the agent in the environment.
- Action(a): a step taken by the agent in a particular state.
- Rewards: for every action, the agent receives a reward and penalty.
- Episodes: the end of the stage, where agents can’t take new action. It happens when the agent has achieved the goal or failed.
- $Q(S_{t+1}, a)$: expected optimal Q-value of doing the action in a particular state.
- $Q(S_t, A_t)$: it is the current estimation of $Q(S_{t+1}, a)$.
- Q-Table: the agent maintains the Q-table of sets of states and actions.
- Temporal Differences (TD): used to estimate the expected value of $Q(S_{t+1}, a)$ by using the current state and action and previous state and action.

2) Working of Q-learning:

Q-learning working by using the example of a frozen lake is shown here. In this environment, the agent must cross the frozen lake from the start to the goal, without falling into the holes. The best strategy is to reach goals by taking the shortest path.

Q-Table: The agent will use a Q-table to take the best possible action based on the expected reward for each state in the environment. In simple words, a Q-table is a data structure of sets of actions and states, and we use the Q-learning algorithm to update the values in the table.

Q-function: The Q-function uses the Bellman equation and takes state(s) and action(a) as input. The equation simplifies the state values and state-action value calculation from Eq. 4.

C. Deep Q-learning algorithm

This is an advanced version of the vanilla Q-learning algorithm where Deep Neural Networks (DNN) are integrated to for generating the Q-table. The steps followed are:

1) Initialize the Target and Main neural networks

The way the Q-table is implemented distinguishes Vanilla Q-Learning from Deep Q-Learning. Importantly, Deep Q-Learning uses a neural network in place of the conventional Q-table. A neural network maps input states to (action, Q-value) pairs instead of a state-action pair to a q-value. The utilization of two neural networks in the learning process is one of the intriguing aspects of Deep Q-Learning. The architecture of these networks is the same, but their weights vary.

The weights from the main network are replicated to the target network every N steps. The learning process is more stable and the algorithm learns more efficiently when both of these networks are used.

Input states are mapped to a pair of (action, q-value) by the main and target neural networks. In this instance, the q-value of each action, represented by an output node, is a floating-point number. Keep in mind that the output nodes will not add up to 1 because they do not represent a probability distribution. In Fig. 2, for instance, one action has a Q-value of 8 and the other, a Q-value of 5.

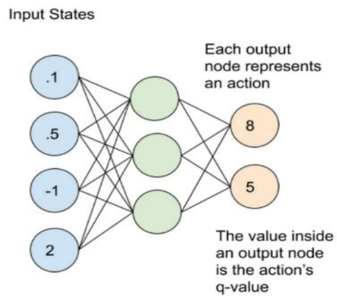


Fig. 2.A simple DQN architecture with notations

Choose an action using the Epsilon-Greedy Exploration Strategy

In the Epsilon-Greedy Exploration strategy, the agent chooses a random action with probability epsilon and exploits the best-known action with probability (1- epsilon).

How to find the best-known action from the network?

The mapping of input states to output actions is shared by the Main and Target models. The model's projected Q-value is really represented by these output actions. In this instance, the most well-known action at that state is the one with the biggest anticipated Q-value.

Updating network weights using the Bellman Equation

The agent must now execute the selected action and update the Main and Target networks. Experience Replay is a tool used by Deep Q-Learning agents to update the Main and Target networks and learn about their surroundings. [22].

D. LTEV2VSim Simulator

The LTEV2Vsim is a dynamic simulator, written in MATLAB, designed for the investigation of resource allocation in LTE-V2V networks, with focus on the cooperative awareness service. Since version 3.0, LTEV2Vsim also allows to simulate the cooperative awareness service using IEEE 802.11p/ITS-G5.

Before version 5.0, the simulator was based on a "beacon period" timing, which was a trade-off between accuracy and speed. Starting from version 5.0, the time granularity has been reduced to 1 ms in order to allow simulating more cases, including traffic generation with non-uniform-periodic characteristics. Additionally, whereas before version 5.0 there were two separate main files for LTE-V2X and IEEE 802.11p, since version 5.0 there is a single main, allowing simulating both technologies at the same time. Version 5.4 (uploaded in October 2020) comes with a number of improvements related to both sidelink LTE-V2X and IEEE 802.11p [17].

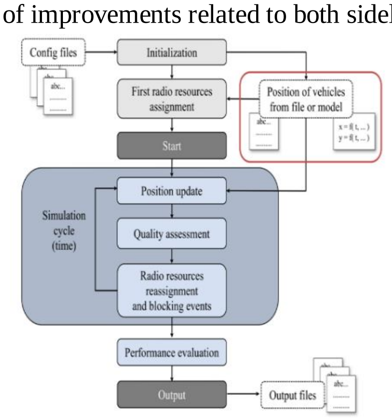


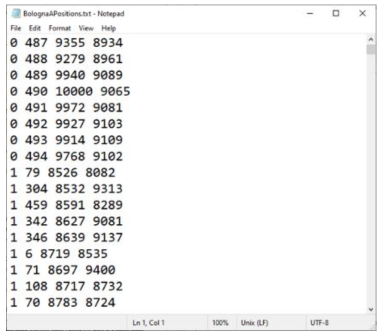
Fig. 3.LTEV2VSim working

Fig. 3 explains the simulator workflow. It starts with providing config files that are road environment considered for vehicle to be simulated as travelling on it. Then, certain traffic model can be chosen which will initialize the number of vehicles, its motional parameters. Resource allocation will be done between vehicles and simulation cycle begins. The three steps of getting the position update of vehicle, observing the quality of messages transmitted or received by the target vehicle and if required, reassignment of radio resources will be implemented till the simulation cycle ends. At the end, excel sheets and MATLAB CLI output displays the performance metrics of the communication protocol [17].

First steps in LTEV2VSim:

- Enabled IEEE 802.11p technology, where by default doesn't support Resource Allocation algorithms, this would not affect the analysis.
- Figuring out the config files; how to edit the map co-ordinates, what all data points are available.

An example Traffic Traces map positions file is shown in Fig. 4 which has co-ordinates of the road lanes present in the map file.


BolognaAPositions.txt - Notepad
File Edit Format View Help

```
0 487 9355 8934
0 488 9279 8961
0 489 9940 9089
0 490 10000 9065
0 491 9972 9081
0 492 9927 9103
0 493 9914 9109
0 494 9768 9102
1 79 8526 8082
1 304 8532 9313
1 459 8591 8289
1 342 8627 9081
1 346 8639 9137
1 6 8719 8535
1 71 8697 9400
1 108 8717 8732
1 70 8783 8724
```

Ln 1, Col 1 100% Unix (LF) UTF-8

Fig. 4.Traffic traces file

Fig. 5 is the MATLAB command line terminal output which displays the packets blocked, packets with error and packets correctly sent in the ratio format.

```
Average number of vehicles in the scenario = 400
*** In the range 0-100:
Average neighbors 19.47 +- 4.10
Blocking = 0.00000  Error = 0.01192 Correct = 0.98808
```

Fig. 5.MATLAB CMD line output

E. Building and training the RL model with DQN Agent

The RL model considered for the vehicle message transmission optimization will involve two entities: an agent and a critic.

The critic is designed a neural network that works in the framework that involves equations (1)-(3) to analyze the environment of the vehicle that is travelling and decide on the parameter value. The network design is done using MATLAB Reinforcement Learning Designer app, with easy UI for engineers to build their customized networks. The proposed network has 5 layers with fully connected and ReLU layers acting as the hidden layers. Once it is defined, the network can be analyzed to find any errors before training starts. Fig. 6 gives the table of layers of the Critic.

	Name	Type	Activations	Learnable Sizes	State Sizes
1	input 225×225×1 input with format 'SSC'	Input	225(S) × 225(S) × 1(C)	-	-
2	fc 50 fully connected layer	Fully Connected	50(C) × 1(B)	Weights 50 × 50625 Bias 50 × 1	-
3	relu ReLU	ReLU	50(C) × 1(B)	-	-
4	fc_1 10 fully connected layer	Fully Connected	10(C) × 1(B)	Weights 10 × 50 Bias 10 × 1	-
5	relu_1 ReLU	ReLU	10(C) × 1(B)	-	-

Fig. 6.Critic NN model

The agent parameters are set with values that will not overfit the model to generate the errors or decrease the performance. Table 7 gives the parameters with the values set for both agent and training process. After values are set, the training begins with reward values that are observed for every episode and validating the training model with Q0 metric. Fig. 8 gives the training progress window of the DQN agent.

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TABLE I. DQN AGENT AND RL TRAINING PARAMETERS

Agent Hyperparameters	
Sample Time	1
Discount Factor	0.99
Batch Size	64
Experience Buffer Length	10000
Critic Learn rate	0.01
RL Training Options	
Max. Episode	500
Max. Episode Length	500
Average Window Length	5
Stopping Criteria	AverageReward
Stopping Value	200

IV. RESULTS

The PDR and CBR are found from the simulations in LTEV2VSim. The trained DQN model is loaded in the MATLAB simulation script. The config file named “Intmap.cfg” is called that has a list of parameters, which includes power and data rate that will interact with the RL model is written in it. Then, using this file name as argument, the LTEV2VSim function is run. The progress can be tracked in the MATLAB CLI. Once the simulation of the traffic with RL model, the excel sheets are generated in the output folder.

From [12], a new multi-objective optimization approach was proposed. Here, the authors have considered BBPSO (Bare Bones Particle Swarm Optimization) method for three parameters: contention window (W), power (λ) and data rate (R_d) which is dynamic in order to maintain the QoS. This is compared with our proposed RL model technique. Fig. 7 and 8 depict the plots of PDR and CBR respectively. Both metrics show that RL model is performing better with PDR around 15% higher and CBR being in the range 0.65-0.56.

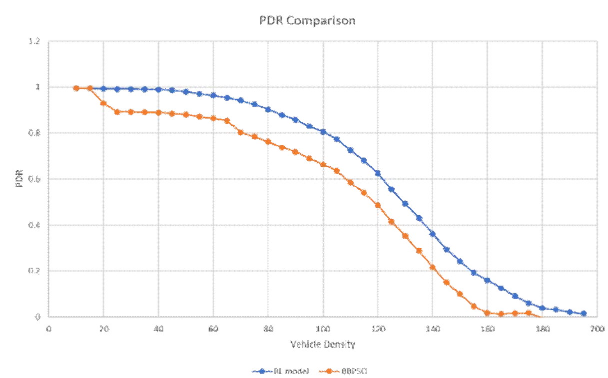

Fig. 7.PDR plot comparison

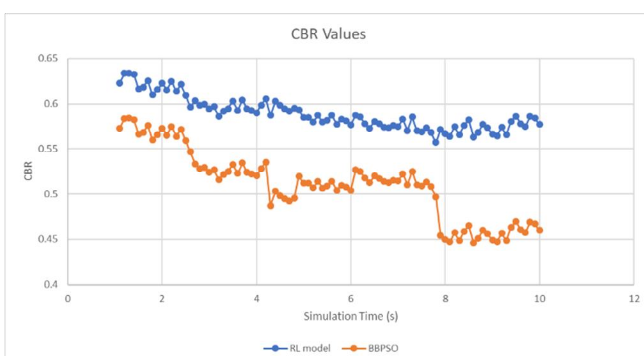

Fig. 8.CBR plot comparison

V. CONCLUSION AND FUTURE WORK

The project demonstrates the benefit of solving the NP-hard conventional problem of finding the optimal data rate and power values for the BSM to be transmitted by the ego/target vehicle to other surrounding vehicles. Here, using MATLAB's RL Designer toolbox and LTEV2VSim to act as a vehicle simulator, the decision making of RL model is observed. The proposed RL model was compared with the existing work of using BBPSO algorithm as an optimization method to improve the vehicle's decision taking on the message transmission parameters. The results found out that the proposed model had performed better in PDR and CBR was efficiently used within the suitable limits.The work could be further taken up to check the RL model's feasibility in working efficiently in various random intersection scenarios and traffic models.

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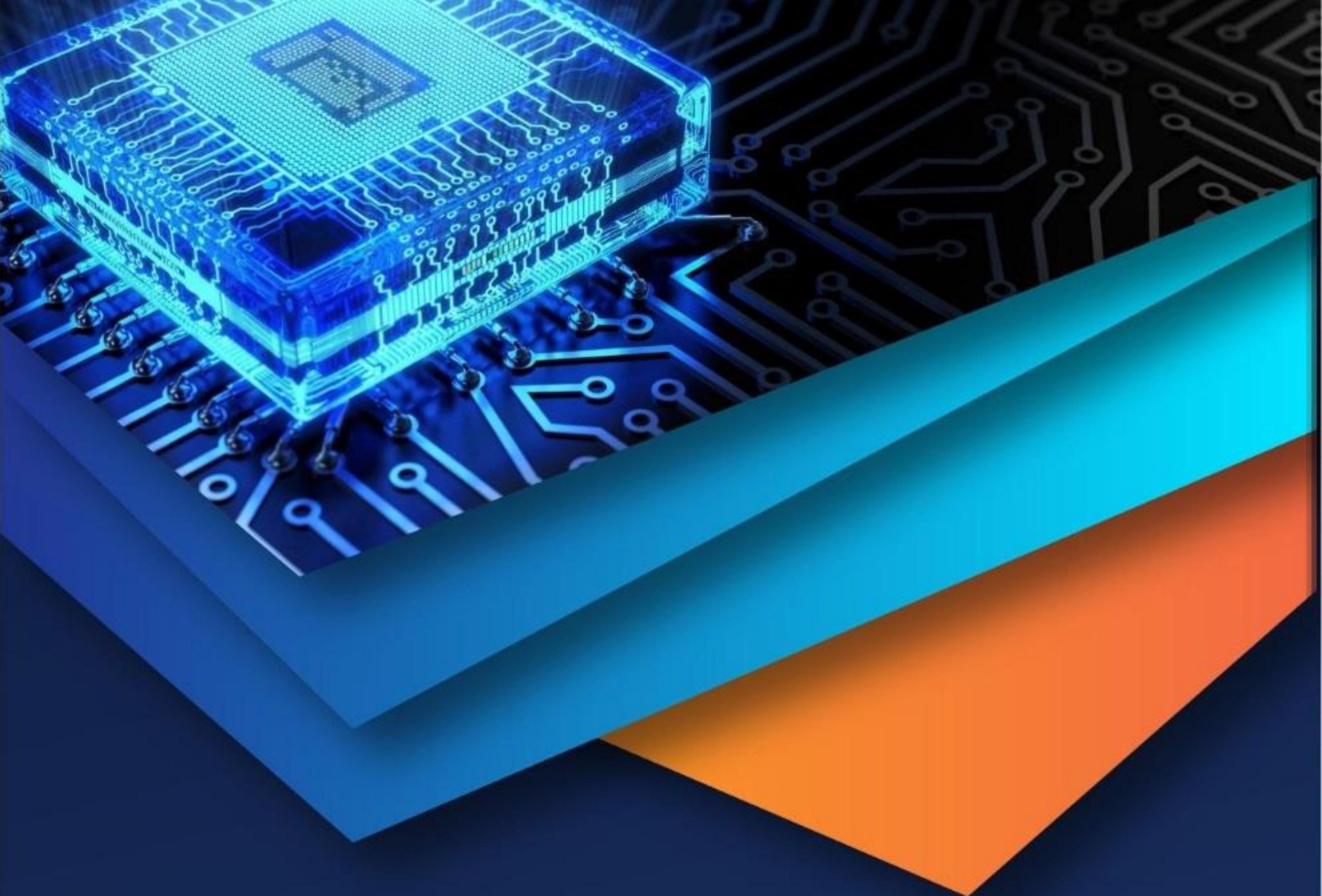

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