Framework of Infotainment using Predictive Scheme for Traffic Management in Internet-of-Vehicle

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***Abstract*—Infotainment system potentially contributes towards controlling accident fatalities in the era of Internet-of-Vehicles (IoV). Review of existing system is carried out to find that irrespective of various methods towards infotainment system, the quality of data being retrieved as well as issues associated with power and traffic congestion in vehicular communication is still an impending challenge. Therefore, this manuscript introduces a novel predictive scheme that offers enriched set of information from the environment to assists in decision making. Reinforcement learning is adopted for controlling traffic signal and power while the proposed system introduce augmented Long Short Term Memory scheme in order to predict the best possible traffic scenario for assisting the infotainment system to make a precise decision. The simulation is carried out for proposed system with existing learning schemes to find out proposed scheme offers better performance in every respect over challenging scene of an IoV.**

Keywords*—Infotainment system; internet-of-vehicle; reinforcement learning; decision making; power; long short term memory

I. Introduction

The concept of vehicular communication system arrives from vehicular adhoc network two decades back in order to facilitate comfortable and safer driving experience [1]. However, owing to the complex structural implementation and various problems associated with such forms of adhoc network, a reliable and safer communication cannot be guaranteed. So, the most recent innovations of Internet-of-Things (IoT) have introduced an Internet-of-Vehicle (IoV) system that is mainly formed to minimize the event of fatal accidents on road [2]. This is carried out by installing IoT objects within the vehicle which is known to facilitate various functionalities. One such form of system which creates a bridge of communication between the vehicle and external entities is infotainment system [3][4]. The contribution of infotainment system is quite significant especially when deployed over an IoV with respect to essential data transmission [5]. It doesn't only pertain to data transmission based on real-time data, but it also carry out various analytical operation to judge the traffic system. This analyzed outcome is disseminated to drivers via infotainment system in order to ensure safer driving over road [6]. A study shows that out of all deaths happened in country of Sri Lanka, maximum of deaths were due to road accidents [7]. Among the road accidents, maximum of them occur during morning hours of 9:00 AM to 10:00 AM and also during evening hours of 6:00 PM to 7:00 PM [8]. This clearly indicates that during rush hours, there will be more accidents and fatalities. Hence an efficient traffic management system is required to manage the traffic and avoid congestion and ultimately accidents. The travel time of the emergency vehicles is also an important factor. It is shown that risk of death due to cardiac arrest will increase by 95% during initial 3 hours of time. Hence, the travel time of emergency vehicles should be much lesser compared to travel time of ordinary vehicles. The infotainment system can be used to transfer vital information and entertainment information together. Since the Infotainment system is aware of GPS co-ordinates and health information of the vehicle, the same information can be used to perform several important tasks e.g. redirecting the driver to roads which have less traffic congestion with connected Infotainment system this can be used to manage entire city's traffic. CityFlow provides an excellent platform for simulating city's traffic and urban mobility in general [9]. The CityFlow platform is built in python and is 20 times faster than the other popular alternatives [10]. It is also found to be compatible with Reinforcement Learning (RL) techniques and hence it can be used along with RL agents. Reviews show that studies towards infotainment system and IoV still demands lot of improvisation that motivates to carry out proposed study.

The proposed study presents a unique computational framework of an infotainment system that is meant for data dissemination over congestion-free traffic using machine learning. The contributions of this study are: i) a unique traffic model is implemented for an IoV considering power consumption, ii) a better traffic management is presented to control power and traffic signaling operation in distributed manner applicable for an IoV operation, and, iii) an analytical model is built which is responsible for carrying predictive analysis of data dissemination for infotainment system with an effective decision making system considering the dynamicity of practical IoV environment. The organization of the manuscript is as follows: Section II discusses about existing investigation towards infotainment system followed by research problem highlights in Section III. Briefing of adopted research methodology is carried out in Section IV while an elaborated discussion about the system implementation is carried out in Section V. Discussion of Result analysis is carried out in Section VI while conclusive remarks of proposed contribution is carried out in Section VII.

II. Related Work

This section discusses about the existing studies being carried out towards IoV with a special emphasis towards infotainment system supportability. Recent studies towards IoV have been reviewed with respect to various methodologies and its effectiveness is studied.

The recent work carried out by Wu et al. [11] has constructed a hybrid communication system which mainly targets towards energy-efficient data transmission system using infotainment. The study also introduces a selection of cache nodes for all the intelligently connected vehicles. The limitation of the study is associated with non-inclusion of spatial complexity associated with streaming over such caching system. Adoption of machine learning towards communication system via infotainment system is carried out by Xu et al. [12] where a reinforcement learning algorithm has been used. The purpose is to encapsulate fluctuating patterns of channel condition in order to select a specific frame. The limitation of the study is that it emphasizes mainly on achieving throughput without consideration of vehicle density or emergency condition. Din et al. [13] have developed a caching system which assists in placing an appropriate content over the target vehicle. The limitation of this model is its non-consideration of uncertain traffic situation which could adversely affect the caching process. Vasudev et al. [14] have developed a unique communication system that emphasize over the mutual authentication scheme in vehicle-to-vehicle communication system. The limitation of this approach is that it uses cryptographic operation over a constraint device, which cannot be considered over a long run without performing any form of optimization of key management. Benarous et al. [15] have implemented a secure communication scheme in IoV where maintains privacy of location-based services utilized by the vehicles. The limitation of this scheme is that it doesn’t present any identification system towards intruders and implementation is carried out considering known adversarial scenario.

A robust infotainment system over an IoV also demands an efficient resource management scheme as seen in work of Ni et al. [16]. The study uses allocation of resources as well as broadcasting of beacons over arbitrary access points for performing congestion control. However, the limitation of the study is that the model carry out the resource allocation without considering dynamic traffic scenario as well as it doesn’t cater up any emergency services too during communication. Adoption of deep learning is witnessed in work of Chang et al. [17] where a model for accident detection system is developed. Upon detecting the collision, the information is transmitted to cloud-services which release notification. The limitation of the study is that it response time of notification completely depends upon the traffic and priority system, which may fail to cater up emergency transmission of accident notification. Silva et al. [18] have carried out a study towards social IoV system which uses conventional communication system in order to perform exchange of data among the vehicles. The paper concludes that there is still an unsolved problem associated with ethical guidelines about such communication in IoV. The work carried out by Sharma and Liu [19] have addressed the problem of misbehavior detection using machine learning in IoV. The study has used supervised learning model for this purpose. The limitation of this work is it is applicable only for specific attack. The work carried out by Wang et al. [20] has developed a behavioral modelling that predicts the driving strategy for safer driving. However, this model completely lacks associating with traffic system in order to exchange such information using infotainment system.

The work presented by Qureshi et al. [21] has presented a mechanism of data propagation using clustering approach in IoV. The method calls for a selection of a cluster head using self-assessment approach as well as routing attributes for data exchange within one-hop nodes. The limitation of this paper is that it consumes too much time in clustering process and does leads to delay in case of heavy traffic in IoV. The work carried out by the Fu et al. [22] have presented a transcoding operation for multimedia streaming in IoV over fog computing. The study uses a reinforcement learning scheme which assists in optimizing the allocation of an appropriate resource for facilitating streaming in IoV. The limitation of this work is its it cannot be used for large stream of data in dense traffic. Mechanism of content caching is implemented in work of Xue et al. [23] where a dynamic programming has been used for minimizing the problem of content caching in data transmission of vehicular network. Irrespective of reduced delay, the study model suffers from poor scalability issues in presence of massive number of vehicle density as well as there is no scheme for prioritization of certain vehicle that seems quite impractical. Existing system has also witnessed modelling of task orchestration in vehicular network as reported in work of Sonmez et al. [24]. The study has used machine learning approach considering the success score of task completion. However, the limitation of the study is its non-inclusion of traffic-lights or centralized controlling system, without which the model is not practical to implement. Hong et al. [25] have presented a cost optimization based scheme using analytical framework in order to enhance the transmission time in IoV network. The model suffers from pitfall of using static threshold for cost, which is impractical in real-world traffic. The work carried out by Hou et al. [26] has used Q-learning-based strategy for content management in IoV. Although, the model is capable of making prediction for movement of vehicle, it doesn’t have any inclusion of multiple path decision over urban traffic. Apart from these, there are various work carried out by Xia et al. [27], Su et al. [28], Ni et al. [29], and Heo et al [30] towards improving communication system with respect to infotainment system in an IoV.

Existing approaches discussed about offers a claim to better outcome; however, they are also associated with some significant issues. The next section outlines the research problems explored from this review.

III. Motivation for the Research

- The traffic congestion is a daily day problem especially in a country like India. The traffic congestion can be easily mitigated with the existing infrastructures and roads. The issue is not of the infrastructure but of the poor management of the infrastructure. Hence an efficient system needs to be designed to manage all the infrastructure and get a better results for the same.

- The connected vehicles are no longer a dream of the future. With several car companies like Tesla and Morris Garage supporting the connected cars by default, the system does not require a hardware upgrade anymore. The computing power of the cars is more than the horsepower of themselves as of now. Since the computing power already exists in the car they only need a software update to support the smart Internet of Vehicle infrastructure now a days.

- The Road accidents due to congestion are a serious cause of the concern now a days. With the systems like autopilot from tesla and several other cutting edge technologies, it is possible to automatically redirect the city's traffic easily with the modern technological systems. And hence there is a scope for a system that can plan the city's traffic and redirect it to a suitable destination on the go.

- The heart attack and other serious emergencies must be addressed immediately. There is a limit to which people cooperate with the emergency vehicles. Green corridor is a very much common phenomenon in cities where an emergency vehicle is given zero traffic and fully allowed to pass through. This is traditionally done for VIP vehicles. However for the genuine emergency vehicles, people give way with understanding. This is possible to be modified based on traffic signal where the emergency vehicles can be made to reach destinations much faster that they are now.

- The Infotainment systems make the driving experience less of a hassle but more of an enjoyable experience. This can be achieved with the proposed study.

IV. Research Problem

After reviewing the existing system in infotainment system in IoV, following are the open end problems identified in proposed study:

- Restricted Coverage Issues in IoV: The conceptual definition of an IoV calls for an interconnected vehicles; however, they still have a dependencies towards a fixed infrastructure at one point. It could be in the form of a hotspots mounted on road or embedded within traffic signal in order to guide the vehicles for congestion free direction. However, the existing studies don't report to consider this coverage issue from Road Side Units (RSU) and mainly focus on vehicle to vehicle communication. This is incomplete implementation for any IoV system to assists the infotainment system within the vehicle.

- Non-inclusion for Density Monitoring: Majority of existing studies on IoV and infotainment system fixes the number of vehicles on specific route. However, in real-time, there are fair possibilities of either increase or decrease of such density over an uncertain instance of time. Without this consideration, the infotainment system will either faces congestion issue or face scarcity of information to undertake decision of data transmission.

- More Focus on Navigation: Majority of existing studies towards infotainment system only focuses on route navigation, whereas infotainment system can also be used for various other forms of data transmission at same time. This requires a dedicated and congestion-free communication channel to be explored by the infotainment system in vehicles. Even if this concept is implemented within present state of implementation in infotainment system, it will significantly cause a serious bottleneck condition for the traffic among the vehicles.

- Less Emphasis towards Data Quality: In IoV system, there are numerous numbers and types of data being required to fulfill the process of data dissemination within an infotainment system. Although usage of mobile edge computing and cloud services makes the operation easier, but still there is a serious pitfalls of almost all the existing architecture of data transmission in IoV. This generates a massive set of traffic data which pertains to road attributes as well as vehicle attributes. Apart from this, there is also a need of multi-objective function to develop a model, which can extract only the productive traffic-related information within IoV system. Hence, ensuring data quality is quite a challenging scenario within current state of infotainment system.

- Uses of Sophisticated Technique: Existing system adopts sophisticated technique targeting for data transmission within vehicles ignoring the resource efficiency of the infotainment system. Adoption of machine learning demands higher training, which is again not much reported to be resource friendly for all implementation carried out in IoV till date.

Therefore, it can be seen that above mentioned issues do exist in present time of IoV deployment scenario. From practical viewpoint, this problem is much dominantly seen in a road network R_n with multiple junction point. It is because of the decision to find the optimal path owing to the problems identified in this section. Therefore, the prime problem formulation of the proposed system can be stated as follow:

$$R_n(S) \rightarrow [opt(r_i)] \asymp A_i \quad (1)$$

In the above problem formulation, the core idea is to obtain a better form of road network R_n for all state attributes associated with intersection points. The idea is to optimize the set of reward r_i parameters for all the set of actions A_i considered in environment of IoV.

This problem is tackled by developing a computational framework that implements a conditional logic for vehicles considering its properties. Further reinforcement learning approach is used to redefine various state attributes that resolves the decision making problem further using LSTM attention network.

V. Research Methodology

The core aim of the proposed system is to design and develop a smart traffic system which is capable of facilitating enriched information to the infotainment system embedded within the vehicle in IoV. Adopting an analytical research methodology, the proposed system make use of machine learning approach in a unique manner which assists in better decision making in the form of direction as well as seamless data transmission in IoV. The proposed system emphasizes more on data quality, where data is associated with both traffic and vehicles in order to assist the infotainment system to undertake correct decision of route formation and resource-efficient seamless data dissemination in IoV. The architecture developed for this notion is highlighted in Fig. 1 as follows:

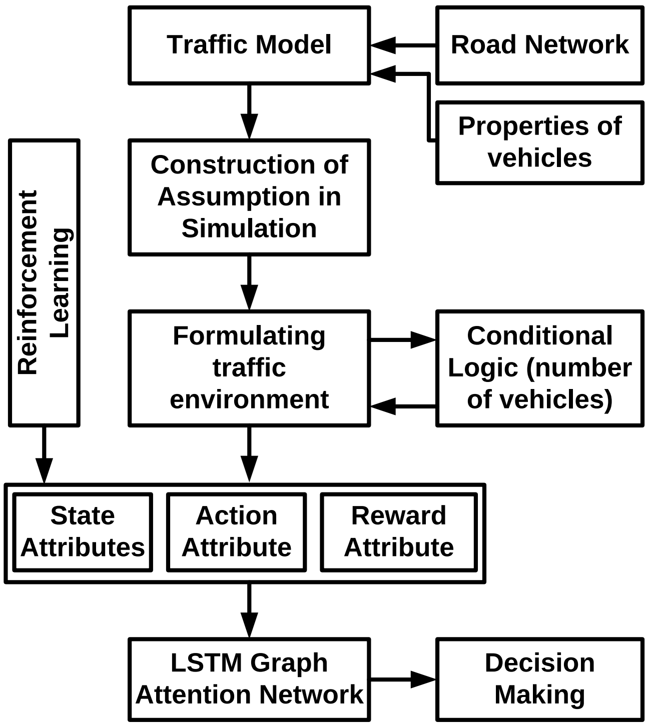

Fig. 1. Architecture of Proposed System.

According to Fig. 1, the proposed system develops a traffic model that mainly consists of formation of road network and properties of vehicle. The proposed modelling considers various attributes in order to develop the topology of traffic model. Further the proposed scheme also constructs assumption which is used for simulation study followed by considering all the essential challenges involved in developing this model. A traffic environment is formed where specific conditional logic is constructed. The proposed system makes use of reinforcement learning scheme which is used over framing up state attributes, action attributes, and reward attributes. Further, Long Short Term Memory (LSTM) graph attention network is utilized which is basically used for decision making towards opting for congestion free and reserving resources while performing vehicular communication in IoV. The next section elaborates further about the operation being carried out by each block towards infotainment system.

VI. System Implementation

In order to design an infotainment platform/scenario, it is required to realize that all vehicles in IoV are required to be strongly interconnected with each other in order to make a seamless transmission. There might be some vehicles connected directly to internet via 4G/5G; however it is required to ensure that the connectivity is given to all vehicles in order to ensure transmission of vital data like traffic and emergency data. Before simulation of the infotainment system itself, the traffic and the congestion is needed to be simulated first and therefore the proposed system is simulated using standard CityFlow simulator [9]. This section discusses about the various aspects of the system implementation.

A. Traffic Model

In order to simulate the traffic scenario, A road network R_n with 4 junctions as $\{J_1, J_2, J_3, J_4\}$ is considered with three level of congestion as i) highly congested, ii) moderately congested, and iii) less congested. The model defines a vehicle V with characteristic elements from the set of properties viz. length, width, maximum positive acceleration, maximum negative acceleration, usual positive acceleration, usual negative acceleration, minimum gap, maximum speed, headway time. The brief highlights of these properties are as follows:

- Length refers to the length of vehicle including the luggage space and bumpers.
- Width of vehicle refers to physical width of the vehicle including mirrors.
- Maximum positive acceleration is the change in speed of the vehicle when accelerator is applied in full throttle.
- Maximum negative acceleration is change in speed of the vehicle when sudden break is applied.
- Typical positive acceleration is the usual acceleration of the vehicle.
- Typical negative acceleration is usual change in speed occurred when breaks are applied.
- Minimum gap is recommended gap that should be maintained between the vehicles.
- Maximum speed is top speed of the vehicle.
- Headway time is the time taken by the following vehicle to reach the position of leading vehicle.

B. Assumptions on Traffic Simulation

The assumptions being considered while developing the proposed schema of infotainment are as follows:

- Everyone respects traffic rules and lane discipline.
- It is assumed that no mishaps happen like accidents.
- All roads are in good condition.
- There are no two wheelers and three wheelers. All the vehicles are assumed to be cars or emergency vehicles.
- Everyone tend to move at similar speeds.

Another, important properties defined for a vehicle are: {Interval, Start time, End time} with default values of {5.0, 0, -1} respectively. These values are considered using 5.0 Likert Scale which signifies 5 as highest and -1 as lowest score. The design process of the model defines a definite simulation time (T_s). If the start time is equal to zero, it means that at the beginning of simulation, the vehicles will appear at their respective junction, however if the end time is equal to -1, it means that it is uncertain to say that when again a particular vehicle will re-appear on the same junction. Moreover, if the interval is defined say interval=5, it means that at every 5 units of time, that vehicle will re-appear on respective junction.

C. Challenges of Modelling

In the present study, the problem is being formulated as a Markov chain model. Each intersection in the system is controlled by an agent. The infotainment system which is present within the vehicle is an embedded system hence it only has a routing table to forward the information. Since all the information is encrypted only the end node can see the required information. SNR of the multimedia signals are noted at the cars and average SNR is calculated. SNR is calculated for 4 different types of data viz. i) text data, ii) video data, iii) audio data, and iv) security data.

D. Traffic Environment from CityFlow

The CityFlow simulator is used to generate the traffic data for three years' time period. Apart from the traffic scenarios of junctions and vehicle characteristics, the program (simulator) also keep adding vehicles with random start time and end time parameters over the span of simulation. Hence, the number of vehicles on the roads keep increasing and creates a dynamic and uncertain stage of congestion. In addition the simulator is internally programmed to model seasonal traffic in such a way that the number of vehicles on the road will be comparatively lower in the month of July and august due to rainy season. The problem of mitigating the congestion, require information as in the Table I.

In the Table I, the parameter of MED is computed as following expression (1),

MED (S)=

$$\begin{cases} S\left[\frac{1}{2}\times\left(\sum_{J=1}^{n} V_J\right)\right] & \text{if number of vehicles are even} \\ \frac{S\left[\frac{1}{2}\times\left(\sum_{J=1}^{n} V_J - 1\right)\right] + S\left[\frac{1}{2}\times\left(\sum_{J=1}^{n} V_J + 1\right)\right]}{2} & if\ number\ of\ vehicles\ are\ odd \end{cases} \quad (1)$$

TABLE I. FORMULATION USED IN PROPOSED STUDY

Junction ID	Total number of vehicles	Speed	Congestion
{J1,J2,J3,J4, .. Jn}	$\sum_{J=1}^{n} V_J$	MED (S)	$\left(\sum_{J=1}^{n} V_J, speed = 0 \Big/ \sum_{J=1}^{n} V_J\right) \times 100$

E. Formulating State Attribute

State is definitive term that represents the state of the particular intersection. Since it has multiple values, it is represented in form of a vector *S* as follows,

$$S = \{\overrightarrow{S_1}, \overrightarrow{S_2}, \overrightarrow{S_3} \ldots \overrightarrow{S_n}\}$$

$$\overrightarrow{S_i} = [L_q, P] \quad (2)$$

In the above expression (2), the variable L_q represents the average queue length of the intersection that is mathematically represented as follows,

$$L_q = \frac{1}{4}\sum_{i=1}^{4} u_i \quad (3)$$

u_i is the queue length of the individual road in the intersection.

F. Formulating Actions Attribute

Actions are execution attribute that Reinforcement Learning RL agent can perform on the environment. Since a single RL agent is assigned to an intersection, there are possibilities of *n* number of actions *A* as follows,

$$A = \{A_1, A_2, A_3 \ldots A_n\}$$

$$A_i = [\overrightarrow{T_i}, P_i] \quad (4)$$

In the above expression (4), the variable P_i represents the power input of the base station. If the RL agent sets a higher power then the signal can be transmitted further and results in a higher useful information ratio. At the same time, it also results in higher overall power consumption. The first variable in expression (4) is represented as follows,

$$\overrightarrow{T_i} = [X_1, X_2, X_3, X_4] \quad (5)$$

In the above expression (5), the variable X_i represents the traffic signal. Since there are 4 signals in each intersection it is represented by X_1 to X_4 and its generalized form is as follows,

$$X_i \in \{R, Y, G\} \quad (6)$$

In the above expression (6), the variable R, Y, and G represents three different lights in the traffic signal. Red, Yellow and Green.

G. Formulating Reward Attribute

Reward r_i is a real number representing the overall performance of the system.

$$r_i = -\frac{\sum_{i=1}^{4} u_i}{4} - P_i + \frac{\sum_{i=1}^{N} s_i}{N} \quad (7)$$

The RL system proposed in this study is programmed in such a way that both traffic congestion as well as information SNR are optimized. The information is passed through a software Defined Network (SDN) created by Mobile Adhoc Networks (MANET) by the vehicles. The parameters which are being optimized here are,

- Useful information ratio of 4 different types of data (varying preference) (MAX).
- Traffic congestion (Average queue length) (MIN).

- Average Travel time of the regular vehicles (MIN).
- Average Travel time of the emergency vehicles (Only ambulances are considered) (MIN).
- Overall Power consumption by the base stations (MIN).

H. *Methodology for Implementing LGAT Neural Network*

The proposed system implements a neural network in the form of regular Long Short-Term Memory LSTM itself; however, one of the hidden layers in this network is common for all the networks over the grid. This essentially makes each neural network to be aware of its surroundings. Hence this is named as LSTM Graph Attention Network (LGAT). LGAT has two parts involved in its module i.e. i) First part which is before the GAT layer and ii) second part is after the GAT layer. Before GAT layer rectified linear unit ReLU Activation function is used whereas after GAT layer, Sigmoid function is used. This is done since the output is always expected to be residing between 0 and 1. The power input of the base station is controlled by considering the input of the percentage of maximum power consumption. The traffic signals are always controlled by considering the input of 1 or 0 to each signal lamp with the one hot encoding strategy. The Adam optimizer is used to train the neural network and the loss function used here is MSE. It should be taken into special attention that MSE is used here instead of commonly used binary cross entropy. This is due to the fact that the network should output an analog value for power consumption in terms of percentage.

Fig. 2 shows the structure of the proposed LGAT neural network where the second hidden layer is the shared layer whose weights and biases are shared with all the other networks. The weight sharing mechanism here is very similar to that of the Siamese neural networks. The output layer contains 13 outputs 12 of which corresponds to the traffic signals and one corresponds to the base station input power percentage.

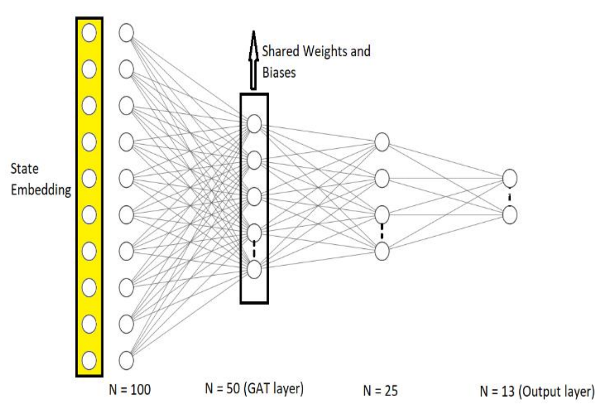

Fig. 2. Structure of Proposed Neural Network.

I. *Training the Agent*

The agent is trained for 4000 episodes in the study and the ANN shown here is trained for one epoch in every episode. Effectively the ANN is trained for 4000 epochs with dynamically changing data. However, since this is an LSTM network, the changing nature of the data is also learnt by the network. The central shared hidden layer enables multiple agents to cooperate with each other. Due to this cooperation the agents are able to produce a good output. Here, the competition behind agents must be avoided at all costs as that will results in selfish agents which may just shut down their base stations in order to save power.

VII. Result Analysis

This section discusses about results being obtained from the simulation study by implementing the proposed scheme discussed in prior section. The recommended hardware and software stack for training the agent are as follows.

- CPU: Intel Core I7 10th Generation.
- GPU: Nvidia GeForce RTX 2060.
- OS: Kali Linux 2021.
- C compiler: GCC 10.2.1.
- GPU C library: Nvidia CUDA 10.1.
- GPU python bridge: Nvidia CuDNN.
- Python: 3.8.2.
- TensorFlow: 2.5.0.

The above-mentioned stack is used in order to get the best results since the TensorFlow works better when it is executed on GPU. Above stack must be used in order to run TensorFlow over GPU. Table II highlights about the properties of vehicles considered for proposed scheme.

TABLE II. Properties of a Vehicle (V)

#	Property	Value	Units
1	Length	5	Feet
2	Width	2	Feet
3	Maximum Positive Acceleration	2	m/sec^2
4	Maximum Negative Acceleration	4.5	$- m/sec^2$
5	Typical Positive Acceleration	2	m/sec^2
6	Typical Negative Acceleration	4.5	$- m/sec^2$
7	Minimum Gap	2.5	Feet
8	Maximum Speed	16.67	m/sec
9	Headway Time	1.5	second

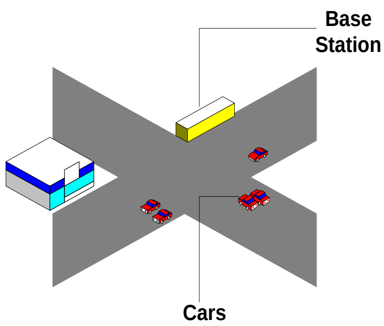

Fig. 3. Simulation Environment.

As it can be observed from Fig. 3 that the simulation is a set up in such a way that there is always a base station in every intersection. Fig. 4 exhibits the higher level overview of system implementation. It is powerful enough to transmit till next base station. However, since the signal strength of the base station can be controlled by the RL agent, the base station's power consumption will vary and the range also varies. If there are vehicles closer to each other, then it is enough if the base station transmits the signal to nearest car. That car can act as a repeater and transmit the message further to other cars. Hence if a particular junction is congested, then the base station may spend less amount of power to transmit the signal further.

The reward depends on both travel time and power consumption. Hence the agent is expected to optimize both of these parameters. The environment is built in such a way that it can support one agent per every intersection. Hence this is a multi-agent environment. Every agent can perform the optimization of power and congestion in their own intersections however, they are expected to co-operate with each other and optimize the entire city's power consumption and travel time of entire city in average.

There are several base stations are present in the city as well as vehicles act as relay to the signal. If the vehicles are far apart, then the base stations have to send signal far hence there will be more power consumption by the base stations. The system must optimize the over power consumption as well.

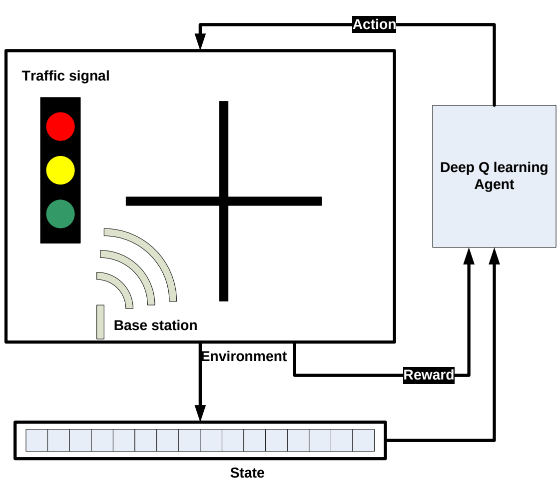

Fig. 4. Higher Level Overview of the System.

Following are the parameters which are being optimized

- Useful Information Ratio: Every vehicle needs to receive the information required for itself. More it acts as a relay, more the battery consumption and lower the bandwidth utilization for itself. Hence base station must provide higher power for better data transmission.
- Queue Length: Queue length is defined as the distance between front of the first stopped car in the intersection to the back of the last stopped car in the intersection (Feet). Traffic congestion is the average of all 4 incoming queue lengths in each intersection.
- Average Travel Time: Average travel time is nothing but average time taken by all cars to travel from source to destination (Entry intersection, Exit intersection). It is considered for Regular vehicles and Emergency vehicles.
- Overall Power Consumption: This is the sum of power consumed by all base stations in the city. The order in which the priority is given to the parameters viz. Travel time of Emergency vehicles, Congestion, Travel time of Regular vehicles, Useful info ratio for emergency data, Useful info ratio for text data, Useful info ratio for audio/video data, Power consumption Simulation parameters are set as following.

Fig. 5 highlights the consideration of 6X6 grid for proposed simulation with 36 intersections in total while there are two simulations done using this layout. Uniflow assumes that the traffic moves in a single direction during morning and opposite direction in the evening. Biflow assumes that the traffic moves in both directions during all times of the day.

Fig. 6 highlights the map to shows the area considered in Hangzhou junction of China. It contains total of 16 junctions and traffic is the real recorded traffic.

Fig. 7 highlights the map to shows the area considered in New York city that contains 196 junctions in total. The proposed system is assessed with existing system of learning-based model of vehicular network in IoV.

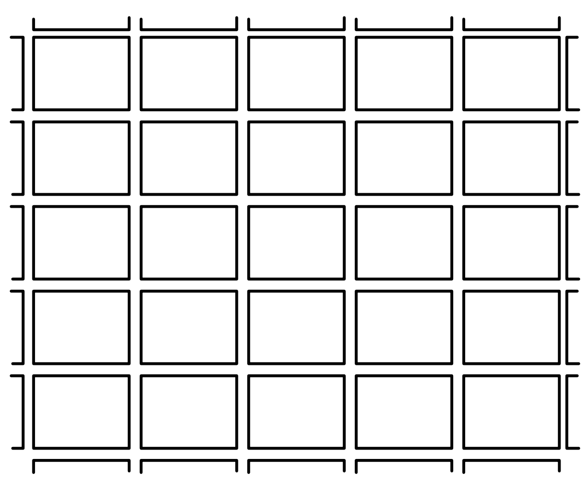

Fig. 5. 6X6 Grid for Simulation.

Fig. 6. Hangzou Simulation Setup.

Fig. 7. New York Simulation Setup.

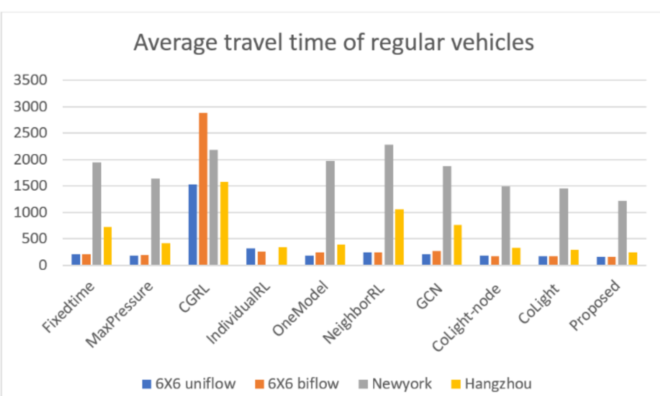

Fig. 8. Average Travel Time for Various Methods.

The above graph in Fig. 8 clearly indicates that the proposed method performs better for every scenario. As it can be observed, New York City is the most difficult scenario. For individual RL, data isn't available. The overall travel time is reduced because of the LGAT architecture. The vehicular traffic follows a particular pattern during the day. LGAT can learn the temporal patterns as well and be able to predict the future vehicular traffic.

An extra parameter which is considered in this study is that average travel time of emergency vehicles (Fig. 9) in which the proposed system is performing better compared to CoLight model. The performance is better in the proposed system since the LSTM layer is used From Fig. 10, can be observed that the travel time of emergency vehicle is half of regular vehicles.

The graph in Fig. 11 shows that the overall power consumption is less for proposed method. This evidently shows that proposed system has better performance score when evaluated with existing CoLight model in perspective of different available dataset of data dissemination in vehicles of urban scenario.

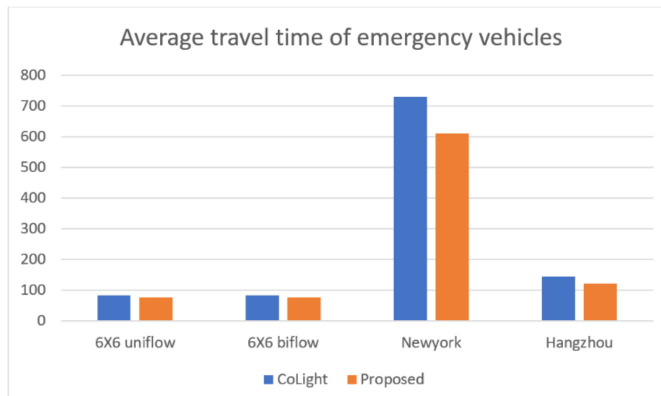

Fig. 9. Comparison of Travel Time for Emergency Vehicles.

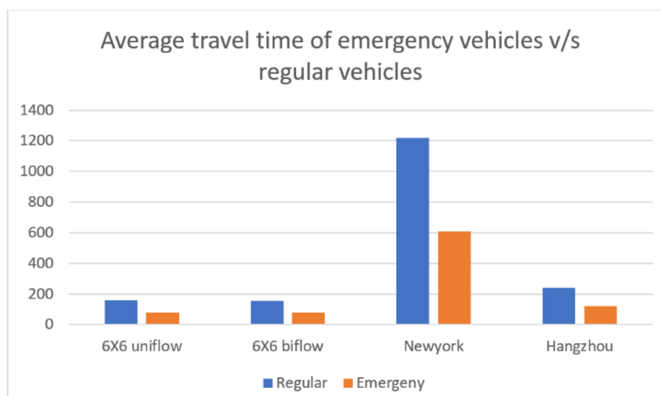

Fig. 10. Average Travel Time for Emergency Vehicle vs Regular Vehicle.

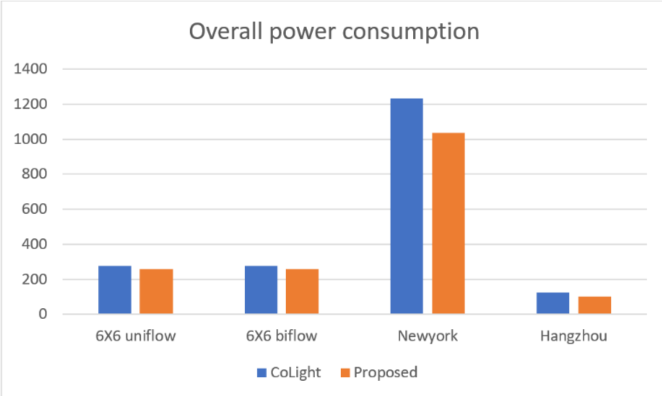

Fig. 11. Overall Power Consumption in MWH.

VIII. Conclusion

This study presents a novel mechanism to manage the urban traffic system and prevents the congestion at the same time. The system can be used to redirect emergency vehicles to shorter paths where there is less congestion and reduce their travel time. The presented model considers the aspect of power consumption by the system. This is carried out in order to address the problem about infotainment system that not only consists of the in-vehicle system but also the sensors, gateways and signal repeaters. Such forms of devices consume a lot of power in order to make sure the quality information is transferred. The implementation of proposed study also optimizes the power consumption by the infotainment system and ensures overall transmission efficiency. The proposed system constructs an optimal environment for the city traffic management and its reward system so that the system rewards the agent based on both power consumption and the travel time. While the environment is a single environment, this is a multi-agent system. An RL agent is assigned at every intersection and they control the traffic signal and power input of the transmitter at the intersection. An agent will also be aware of actions and states of other agents through a novel neural network architecture proposed in this study, LGAT architecture. The proposed system implements an LGAT that is a special type of LSTM in which one of the layer's weights and biases are shared with all other agent's weights and biases. The neural network here uses the DQN architecture for RL. The DQN architecture means the NN takes the action as input and outputs Q values for all possible actions. Q values are nothing but the future rewards for the system. The system is trained over multiple episodes with a single epoch per episode. The proposed study considers several existing methods and considers various parameters to study the traffic. There are two synthetic environments and two realistic environments in this study. The two realistic environments are the traffic data from Network city and Hongzow junction from Hong Kong. The synthetic environment contains two different environments which are 6x6 uniflow and 6x6 Biflow.

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