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RESEARCH ARTICLE

Framework for Simulation of Vehicular Communication using LSTM-based Graph Attention Networks

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Abstract

Objectives: To develop a computational framework which is capable of analyzing the realistic scenario with better decision-making of traffic management using enhanced learning-based model. **Methods:** A discrete baseline architecture is designed for proposed traffic model considering road network and properties of vehicles. A specific set of logical condition is formulated for constructing assumptions required for studies followed by formulating traffic environment. A reinforcement learning scheme is applied in order to obtain state attributes, action attributes, and reward attributes followed by subjecting all the attribute information to Long-Short Term Memory Attention network. The outcome of the model is inform of decision towards proper vehicular communication. The implementation is carried out by two dataset viz. Hangzou data and New York data. The prime parameter for the evaluation is average travel time while the comparison is carried out with multiple standard dataset. The simulated implementation of the proposed scheme is carried out on Hangzou simulation set up where topology for Internet-of-Vehicle (IoV) is executed on top of it. **Findings:** The study outcome exhibited significant improvement in average travel time of emergency as well as normal vehicles assessed with respect to various existing dataset of 6x6 uniflow, 6x6 biflow, Newyotk, and Hangzhou. The study outcome also exhibited Newyork to show approximately 85% of reduced travel time compared to 6x6 uniflow, 6x6 biflow, and Hangzou set up. This outcome was also found in agreement with power consumption where Hangzou set up was shown to offer approximately 96% of reduced power consumption in contrast to Newyork set up. **Novelty:** The proposed study contributes towards yielding a generalized assessment framework for traffic management which is capable of evaluating average travel time and power consumption unlike any existing system in cost effective manner.

Keywords: Vehicular communication System; Internetofthings; Reinforcement Learning; Decision Making; Long Short Term Memory; Graph attention Networks

1 Introduction

The concept of vehicular system was created around 20 years before the proposed work. It was created with the help of wireless ad-hoc networks where each vehicle communicates to one another directly.[1]. However, this poses a challenge in the structure of the communication topology for achieving an efficient communication and hence, the reliability of the communication could be low as well as the critical information may not be passed over such network. Hence, the internet of vehicles (IOV) has been proposed with the main purpose of reducing the accidents on the road. This IOV system is based on the pre-existing Internet of Things (IoT) system[2]. This system is created by installing several IOT nodes in the vehicles. The IOT nodes have the ability to both gather the data and also to communicate. One such system has been previously proposed in order to bridge between vehicular communication system and external entities like base station[3,4]. The contribution of Vehicular communication system is quite significant in the transmission of the critical data in order to avoid concession and thereby avoiding maximum of the road accidents[5]. The communication system not only carryout the communication of traffic data but also analytical data like the oil level and engine health in order to perform various analysis for maintenance of the health of the vehicles. This analyzed information is displayed to the driver in order to ensure the safest driving experience to all the drivers[6]. A survey was conducted in the country of Sri Lanka which shows that among overall deaths happened in that country, maximum of them were due to road accidents itself[7]. Another survey has shown that the road accidents many occur during the time of 9:00 AM to 10:00 AM and also during evening hours of 6:00 PM to 7:00 PM due to the higher number of vehicles on road during these timings[8]. Hence, more fatalities and accidents can be expected during the rush hour. Hence, an efficient traffic management system needs to be proposed in order to not only manage the traffic which is already on road but also to predict the rush hours and plan the traffic management ahead of time. Another important factor that should be considered is the average travel time. Average travel time is nothing but the average time taken for a vehicle to reach its destination from the source.

The travel time of emergency vehicles like ambulance is a serious constraint for traffic management system. It is a known fact that risk of death due to heart attack increases by 95% if the patient is not hospitalized during the first 3 hours of time. Hence, reduction of travel time of emergency vehicle takes preference over reducing the travel time of ordinary vehicles. The Vehicular communication system can be used to transmit critical information as well as the Entertainment information parallelly. Since the proposed system is aware of the GPS coordinates of the vehicle, this information is used to perform several other important tasks like redirecting the vehicular traffic to non-congested roads via driving guidance system present in the vehicles. The proposed system can be used to manage entire city's traffic. CityFlow is only of the simulators available which can be used to simulate the entire city's traffic and also measure and analyze vital data along the process. It is 20 times faster than existing SUMO simulator[9]. The speed is due to the fact that the simulator is built natively on python and doesn't make use of an existing simulator.[10]. The CityFlow is found to be compatible with Reinforcement learning and hence the CityFlow can be plugged into various RL agents in order to measure the performance of one agent over another.

This part of the manuscript discusses the prior research in the field of study specifically in vehicular communication systems with emphasis for traffic management and data transfer efficiency. All the works studied here will help to make the proposed system better. The work carried out by Wu et al.[11] have created a combined method which combines wireless ad hoc as well as a centralized system which focuses on communication for the infotainment systems. The Machine learning was adapted for vehicular communication system by Xu et al.[12] where reinforcement learning approach has been used. However, in this study, the vehicle density, congestion scenarios emergency scenarios like traffic jam are not considered. Din et al.[13] have proposed a intermediate memory cache system which streams appropriate contents to the target devices. Vasudev et al.[14] have developed a unique communication system that emphasize over the mutual authentication scheme in vehicle-to-vehicle communication system. Benarous et al.[15] have implemented a secure communication scheme in IoV where maintains privacy of location-based services utilized by the vehicles. A robust infotainment system over an IoV also demands an efficient resource management scheme as seen in work of Ni et al.[16].

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. 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 work carried out by Wang et al.[20] have developed a behavioral modeling that predicts the driving strategy for safer driving. The work presented by Qureshi et al.[21] have presented a mechanism of data propagation using clustering approach in IoV. The work carried out by the Fu et al.[22] have presented a trans coding 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. 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. Existing system has also witnessed modeling 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. 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 work carried out by Hou et al.[26] have used Q-learning-based strategy for content management in IoV. Apart from these, there are various work carried out by Xia et al.[27], Su et al.[28], Yu et al.[29], and Heo et al[30] towards improving communication system with respect to infotainment system in an IoV.

After going through several existing works regarding Vehicular communication system and Internet of vehicles or IOV, following are the research problems obtained: i) The existing studies don't concentrate on coverage of these embedded wireless units (ESU) and focus only on vehicle to vehicle communication, ii) Majority of the existing studies consider the number of vehicles in a road as a fixed parameter without considering the possibility that the number of vehicles may vary due to varying traffic condition, iii) Most of the existing studies focus on the navigation of vehicles using the vehicular communication system. However vehicular communication system also can be used for communicating other information like emergency vehicle information or vehicle health data, iv) In vehicular communication system numerous data will be aggregated and transmitted via the communication system any error in the transmission may result in huge loss of data, v) Existing systems adopt highly advanced system inside cars itself ignoring the computational resource consumption.

The prime objective of proposed study is to introduce a new system for vehicular communication which can perform wrangling of entertainment data as well as the emergency data. And controls the city's traffic by taking intelligent decisions using machine learning. The contributions of this study are: i) The mode in which the entire city's traffic can be simulated, ii) A better traffic management system where all the ages are cooperating with each other for efficient traffic management, and, iii) the LSTM based mechanism which can predict the future of the traffic and can efficiently handle the traffic.

2 Methodology

The architecture of the proposed system is shown in Figure 1. The Core aim of the proposed system is to design and develop a smart vehicular communication system to enable smart traffic management. The traffic management is done by controlling of the traffic signal lights and redirecting the vehicles towards the less congested roads. The research is carried out by implementing the system over CityFlow simulator. The RL agent is designed as shown in the Figure 1. According to figure, the proposes system develops a traffic simulation environment according to the preprogrammed logic and also the two data sets available for traffic simulation. The two available datasets are, Hangzou data and New York data. This will help the simulator to create a dynamic traffic scenario with the help of data as well as the logic. It is required to simulate changing scenarios of the traffic. The traffic model consists of the structure of the roads as well as the vehicle properties. The vehicle properties are assumed, and they are discussed in detail in section 5. The RL agent used in the study makes use of novel MGAT or Memory Graph attention networks in order to compute and take decisions for the environment. The CityFlow supports multiple agents to be connected at a time. Hence, a single traffic signal is controlled by an agent. Hence, number of agents in the system is equal to number of intersection in the system.

The vehicular communication system design needs to take into account that all the systems must be strongly interconnected with each other and also needs to communicate efficiently with each other. The system implementation also takes into account that multiple neural networks need to be ran parallelly and the traffic scenario needs to be handled. The CityFlow is the best platform to simulate this scenario. The system implementation is carried out in 9 steps in total. The implementation is divided into logical steps. Overall, these steps are carried out to perform the most realistic implementation of the system. The system consists of two types of vehicles, namely ordinary vehicle and emergency vehicles which will be taken into account further. The system is implemented in such a way that it is more efficient in terms of resource consumption as well.

2.1 Traffic Model

In order to simulate the traffic environment a road network R_n is considered with N junctions namely $\{J_1, J_{2,} J_{3\ \ldots}\ J_n\}$ with three different levels of congestion i) highly congested, ii) moderately congested, and iii) less congested. The vehicle V needs to be defined with character specifications such as, 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: i) Length refers to the length of vehicle including all accessories, ii) Width of vehicle indicates total width of the vehicle including side mirrors, iii) Maximum positive acceleration is the change in speed of the vehicle when the accelerator is applied in full throttle, iv) Maximum negative acceleration is the change in speed of the vehicle when breaks are applied suddenly, v) Typical positive acceleration is the change in speed of the vehicle when it is operated in the usual phase,

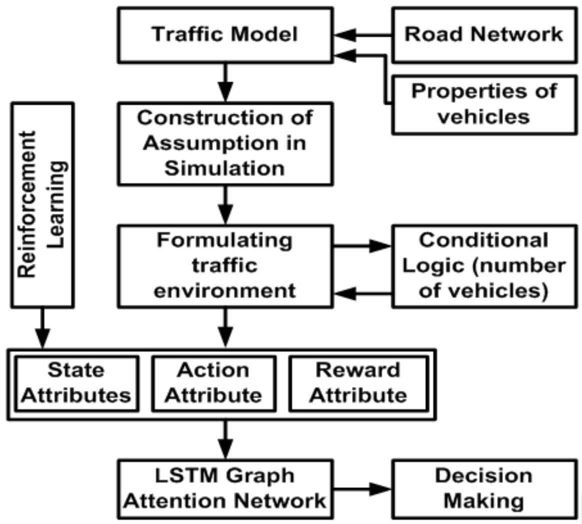

Fig 1. Architecture of Proposed System

vi) Typical negative acceleration is usual change in speed occurred when breaks are applied, vii) Minimum gap between the vehicle is the minimum distance recommended by the law between two moving vehicles. It is assumed that all drivers follow the same, viii) Maximum speed is the highest speed of the vehicle, ix) Headway time is the total travel time of the vehicle from its source to destination.

2.2 Assumptions on Traffic Simulation

Several aspects of the traffic are assumed while simulating the traffic management and vehicular communication system which are: i) All drivers respect and follow the traffic rules and also the lane discipline, ii) It is assumed that no mishaps like accidents happen, iii) Good conditions of the roads are assumed. Meaning it is assumed that roads won't be under repair and won't have potholes, iv) Only cars are assumed to be on road. Even the emergency vehicles are assumed to be cars, and v) All vehicles tend to move at similar speeds. Another important property defined for the vehicle which is: {Interval, Start time, End time} with default values of {5.0, 0, -1} respectively. These values are considered as 5.0 Likert Scale which signifies 5 as highest and -1 as lowest score. The mode defines a 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. However, this process does not influence much to the congestion

2.3 Traffic Environment From CityFlow

The traffic environment is designed using two different aspects in the environment. The first one is where the environment start with the fixed number of cars and environment keep adding the cars randomly at certain time intervals. This creates an uncertain traffic scenario. The system needs to adapt dynamically to the changes and avoid congestion. The congestion is calculated as ratio of the total number of vehicles stopped over total number of vehicles. The equation for the same is as shown in Table 1. The median speed of the vehicle is also an important constraint here as it inversely proportional to the average travel time of all the vehicles. The travel time is desired to be less in the value hence mode median speed is desired.

Table 1. 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)	$\left(\frac{\sum_{J=1}^{n} V_J,\, speed=0}{\sum_{J=1}^{n} V_J}\right) \times 100$

In the above Table 1, the parameter of MED is computed as following expression (1), MED (S)=

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

2.4 Formulating State Attribute

The state is used to represent all observations made in every intersection. State of the particular environment is nothing but a set of states. Each element in the set is nothing but a vector which represent various observations made.

$$S = \left(\overrightarrow{S_1}, \overrightarrow{S_2}, \overrightarrow{S_3} \ldots \overrightarrow{S_n}\right\} \overrightarrow{S_i} = [L_q, P] \tag{2}$$

In the above expression (2), the observations of each intersection are shown. The variable L_q indicates the average queue length of the intersection which is calculated as follows. The queue length is directly proportional to congestion hence if the queue length is optimized the congestion will also be optimized. It is calculated as follows,

$$L_q = \frac{1}{4}\sum_{i=1}^{4} u_i \tag{3}$$

u_i is the queue length of the individual road in the intersection, and P represent the power consumption of the base station present in that intersection

2.5 Formulating Actions Attribute

Actions are the decisions taken by the RL agent. These Actions represent what can be change in the Traffic environment. Since an RL agent is attached to every intersection, Actions are also indicated as a set of actions. Each action is a set of two mode attributes as show in equation 4,

$$A = \{A_1, A_2, A_3 \ldots A_n\}, A_i = \left[\overrightarrow{T_v}, P_i\right] \tag{4}$$

In the above expression (4), the P_i represents the power input to the base station. More the power higher the coverage. However that also results in higher power consumption. For a congested road low power is enough however it also mean that the SNR might be lower. The vector T represent the state of the traffic signal. Each intersection is assumed to be connecting 4 roads hence there are 4 elements in each T vector. It is represented as,

$$\overrightarrow{T_i} = [X_1, X_2, X_3, X_4] \tag{5}$$

In the above expression (5), the variable X_i represents the traffic signal. Each signal may allow the left lane, middle lane or the right lane. The mathematical representation is shown as,

$$X_i \in \{R, Y, G\} \tag{6}$$

In the above expression (6), the variable R, Y, and G represents three different lanes right middle and left.

2.6 Formulating Reward Attribute

Reward r_i is the most important aspect of the system as it decides which variable needs to be optimized. It is represented as,

$$r_i = -\frac{\sum_{i=1}^{4} u_i}{4} - P_i + \frac{\sum_{i=1}^{N} S_i}{N} \tag{7}$$

The RL algorithm in the proposed study must optimize the SNR, Congestion and the power consumption. Higher SNR is desired whereas lower congestion and power consumption are desired. Hence, the reward function is formulated in such a way that the reward reduces with reduction in SNR and reward also reduces with increase in power consumption and congestion. The SNR is measured by the average of ratio of the useful information received by the nodes to the total data received by the nodes. Congestion is not directly used in the Reward function. Instead of congestion, Average queue length is used in the reward function which is proportional to the congestion.

2.7 Methodology for Implementing MGAT Neural Network

The systems makes use of MGAT neural network which is short for Memory Graph Attention network. This network consists of an attention layer with 3 hidden layers which are LSTM layers. LSTM is short for Long Short term memory. The LSTM neurons internally contain a long memory which can store its past inputs as well as the past outputs. Hence, the LSTM can actually predict the future of the traffic scenario and take decisions accordingly. The MGAT in the proposed system is designed as shown in Figure 2. If regular LSTM is used in each and every intersection then the agents will only try to optimize their own intersection, but they won't be aware of the other intersections. These gives rise to a competitive scenario where all the agents compete with each other instead of cooperating with each other. Hence, a GAT or graph attention layer is introducing whose weights and biases are shared between all the agents. If a change occurs in one of the agents then it is reflected in all other agents as well. And hence when they are optimized together, the agents cooperate with each other. The input layers consist of over 100 neurons corresponding to each intersection. Data of each intersection is given to all the networks. The output layer contains 13 neurons where 12 are binary output representing the traffic signals and one is analog output which gives percentage of the power given to base station. The agents are trained for 4000 episodes. During the training the agents not only learn the traffic management but also the changing pattern in the traffic pattern. These patterns help the agents to take decisions based on the future data. The agents cooperate with each other instead of competing since the Graph attention layer will be a common layer. All the agents are trained parallelly.

3 Results and Discussion

This section discusses the results obtained by the experiment and the simulation. Recommended hardware and software for this system is as following: 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. This specification are used as this is the size of a typical vehicles. Emergency vehicles are of same size with a higher priority. The properties of the vehicle are: Length: 5 Feet, Width:2 Feet, Maximum Positive Acceleration: 2 m/sec^2, Maximum Negative Acceleration: 4.5 m/sec^2, Typical Positive Acceleration: 2 m/sec^2, Typical Negative Acceleration: 4.5 m/sec^2, Minimum Gap: 2.5 Feet, Maximum Speed: 16.67 m/sec, and Headway Time:1.5 second. The simulation is set up in such a way that there will be a base station in every intersection. The base station will simply transmit the signals. For a congested road, it is enough if the base station transmits the signal to a nearby car. For a freely moving road, the base station must transmit towards all the cars in the road thereby increasing the power consumption. The car can act as a repeater and can transmit the signals further. The agent controls both the base station power and the traffic signal. The agent is configured in a DQN structure. The simulation environment is set as shown below. For the first two scenarios, synthetic data is used where a 6x6 grid is set up as show in Figure 5. In the first scenario, the vehicles are assumed to be going in a single direction at a time simulating higher density of the traffic towards offices in morning and vice versa in the evening. The second scenario introduces randomness and it shows a biflow environment where the traffic moves in both directions. The proposed system considers 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

Figure 2 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. The analysis uses 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.

Figure 3 indicates that the proposed system performs better than all the existing systems in terms of average travel time of the vehicles. An extra parameter which is considered in this study is that average travel time of emergency vehicles (Figure 4) 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 Figure 5, can be observed that the travel time of emergency vehicle is half of regular vehicles. Figure 6 shows that the overall power consumption is least in case of the proposed system.

The proposed scheme is evaluated with respect to three parameters i.e., resource consumption, computational burden, and overall efficiency. The resource consumption mainly considers the power factor while the computational burden is assessed with respect to presence of iterative operation in stiputaed observation time to accomplish convergence. Overall efficiency assess the performance with respect to response time over increased number of test environment. Table 2 highlights the observation being carried out by comparing proposed scheme with related works.

The radio model discussed in work of Wu et al.[11] offers energy efficiency, but they are mainly carried out their study towards indoor localization and hence this model needs more evidence to prove its applicability over larger scenario. The computational burden is found to be medium as no explicit optimization has been carried out towards standard ellipse-based

Fig 2. Hangzou simulation setup

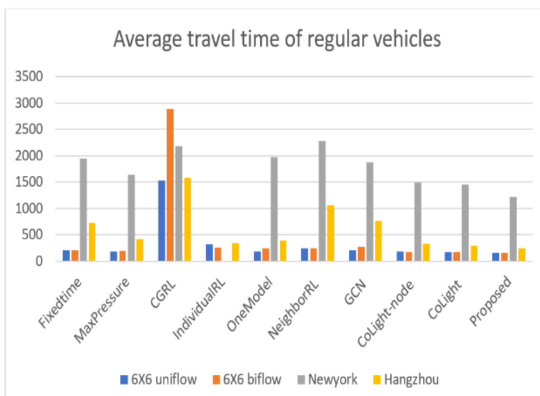

Fig 3. Average travel time for various methods

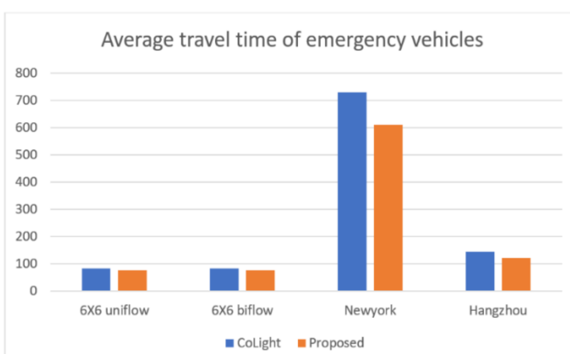

Fig 4. Comparison of travel time for emergency vehicles

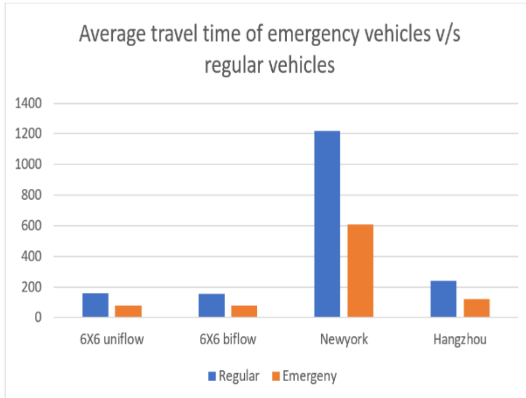

Fig 5. Average travel time for emergency vehicle vs regular vehicle

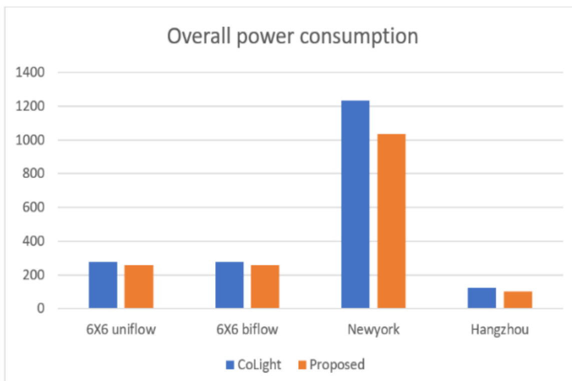

Fig 6. Overall power consumption in MWH

Table 2. Comparison with existing schemes

Approaches	Resource Consumption	Computational Burden	Overall Efficiency
Proposed	Low	Low	High
Wu et al. [11]	Medium	Medium	Low
Xu et al. [12]	High	High	Medium
Chang et al. [17]	High	Medium	Low
Silva et al. [18]	High	High	Low
Sharma & Liu [19]	Medium	Medium	Medium
Wang et al. [20]	Medium	High	Low
Qureshi et al. [21]	High	High	Medium
Fu et al. [22]	High	High	Medium
Xue et al. [23]	High	High	Low
Sonmez et al. [24]	High	High	Low
Hong et al. [25]	High	Medium	Low

modeling presented in the paper.The overall efficiency, however, have chances for betterment of the estimation parameters are revised to outdoor settings. However, this is not the case with proposed scheme where a network modeling is carried out considering constraints of junction point while learning-mechanism is developed to reduce the travel time. Discussion of travel time as parameters is also less reported in existing scheme. The work carried out by Xu et al.[12] have used reinforcement learning for better channel utilization in vehicular communication. Their overall efficiency is medium due to reinforcement learning module for opting resource efficient path; however, their iterative nature potentially introduces computational burden and higher power consumption. Adoption of similar methodology is also noted in work of Fu et al.[22]. It is to be noted that proposed scheme doesn't offer any such outcomes. Owing to better route exploration process, the proposed scheme can also find the resource efficient path but using less iterative steps. Apart from this, owing to memory sharing principle of vehicular nodes, the dependencies of information towards navigation reduces down leading to progressive reduction of power consumption. The protytype design by Chang et al.[17] uses high end configurations towards modeling experimental set up while it has a dependency of various third party application and devices to aggregate primary data of traffic. The best part of this model is to identify the event but the pitfall is towards transmission that depends upon specific model set up with higher resource inclusion leading to degraded power conservation and medium computational burden. Apart from this, this prototype can be used only for local zone of traffic and doesn't assist in given global information of connecting traffic. On the other hand, proposed scheme has acquired the global information of the traffic while learning to scheme can not only assist in furnishing local information for navigation but also seamless dissipation of global information for updating the vehicle. The model presented by Silva et al.[18] have presented an architecture of IoV using social network application in its application layer. The biggest pitfall of this model is its social network data is highly dependent on the user of the device. Even if it is assumed that user forward reliable information about traffic, the system doesn't offer an exclusive decision-making module to offer reliable navigation. This problem is not found in proposed scheme as the learning model is evaluated on multiple set up to confirm its applicability on any form of urban environment over longer transmission zone. The decision-making is carried out only at the event of identified contradiction in the vehicular movement when it transit from one to another state of congestion. Hence, more reliable and practical information can be relayed in proposed scheme. The work carried out by Sharma and Liu[19] have used multiple set of learning approaches in order to identify the anomalies present in network data. The methodology developed are quite dependent on extensive stages of acquisition of data and series of rigorous analytical processing targeting towards meeting its objective in different scale of traffic at the cost of computational burden. Similar problem is also noted in work of Wang et al.[20] and Quereshi et al.[21]. Although, this adoption offers increased accuracy but it also introduces higher computational burden when exposed to large and different form of urban traffic set up. A closer look into proposed scheme maintains both accuracy and computational burden in control owing to its structure. The work carried out by Xue et al.[22] have used dynamic programming along with greedy approach for improving edge caching performance. These options are quite good enough for applying integration of IoV with fog; however, increasing communication data saturates the information maintained by each node and this eventually leads to computational burden. Hence, in the process of route exploration the node will require high power dependency in order to maintain lower delay as seen in its outcome. However, proposed scheme offers a simplified learning mechanism which allocates incentives in order to leverage communication in odd traffic situation and hence the computational efficiency is always maintained higher. Equivalent problems do existing in Sonmez et al.[24] and Hong et al.[25]. It is to be noted that proposed scheme offers a simplified reward attribute without directly using congestion information and it only uses queue information. Therefore, its computational efficiency is always high as it can eventually obtain queue information in order to formulate its reward. Therefore, better scalability and reduced travel time is always maintained with reduced power consumption. Moreover, none of the existing scheme has actually emphasized towards power consumption explicity, which is another novelty of proposed scheme.

A closer look into the methodology of the proposed scheme exhibits that it offers a unique approach towards a computational framework that can carry out traffic management of urban area and thereby it can offer a feasibly practical solutions towards bypassing the bottleneck condition within traffic. The outcomes of the study eventually show that redirection of the emergency vehicular node can be carried out by diverting them over path with shortest distance computed characterized by minimal time to travel as well as minimal degree of bottleneck condition. Different from existing schemes, it can be also noted that proposed scheme considers the consumption of power factor associated with the vehicular traffic management system. The primal reason for this consideration is that a vehicular node consists of multiple equipment that runs over power supply. The outcome shows that proposed scheme can actually distinguish very clearly power consumption for different set-ups very efficient. Although, it is tested for four discrete set up, but it can also be deployed over any set up for analysis of power. The outcome eventually exhibited better power optimization for facilitating efficient transmission over vehicular network. Further, it is also noted that construction of an optimal environment for managing urban traffic has its own benefits in proposed scheme towards this transmission process. Adoption of reinforcement learning to scheme facilitates allocation of rewards to the agents on the basis of reduced travel time and reduced power consumption. It should be noted that proposed scheme is implemented using a multi-agent mechanism although the considered environment is singular in its form. All the intersection position of the traffic is allocated with a reinforcement learning agent that is efficient for managing as well as controlling the traffic signal along with other attributes at the position of intersection. The reduced travel time noted in the outcome is attributed by the awareness of the agent with respect to states as well as actions adopted by agent modules using a unique learning-based architecture system. Another significant learning outcome noted in the evaluation is that proposed scheme could actually optimize multiple observation at same time owing to formation of new form of LSTM where all the biases and weights of an agent are shared with similar entities associated with one specific layers. According to this architecture deployment, a neural network is considered to adopt all the actions in the form of an input while Q-values associated with all feasible set of actions are considered as an outcome. The outcomes are quite consistent owing to the training operation performed over different episodes characterized by unit epoch. Further consistency is noted when the assessment is carried out over artificial environment (6x6 Biflow, 6x6 uniflow) and practical environment (Hongzhou junction and Newyork city).

4 Conclusion

This study presents a method to manage the traffic in urban scenario. This system shows a shorter path to the emergency vehicles in order to reach destination faster. The power consumption is a unique aspect considered in the present study which cannot be seen in the previous studies. The comparison with CoLight is done by adding metrics to the existing system. The proposed system implements the novel MGAT system which not only cooperates with other agents and take decisions, but can also predict the future of the traffic and take decisions based on that.

4.1 The unique significance / novelty of proposed scheme are as follows

- Compared to existing schemes in IoV, proposed scheme offers significantly lower resource consumption over larger environment of vehicular movement.
- The learning-model used in proposed scheme is less iterative compared to existing learning schemes leading to reduced resource consumption and higher overall efficiency.
- The assessment environment of proposed scheme is quite broadened with inclusion of multiple set-ups compared to existing schemes where a singular set up is used to validate the outcome.
- The proposed model is capable of assisting in dynamic congestion scenario with reduced dependencies towards any intermediate infrastructure, whereas majority of IoV has consistent dependencies leading to higher computational burden.

The limitation of the proposed study are that proposed scheme is not engaged in performing authentication of the nodes. Moreover, the model doesn't assess the impact of such node assessment time in the overall travel time or efficiency. Hence, it is an open-end question to find out the possibility of changes in travel time when heterogeneous node authentication is introduced in the model. The prime strength of proposed scheme is its capability to ensure the least travel time irrespective of any degree of node density and queue length and weakness of the model is that it doesn't evaluate the legitimacy of the node to carry out propagation or assess their authorization towards data transmission with specific vehicle. Hence, the future work direction will be to address this pitfall by considering an auditor node, which is a specially selected node with higher resources to authenticate this newly joined node. The idea is to reduce the dependency of Road Side Unit to facilitate longer communication coverage.

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