Edge Computing AI-IoT Integrated Energy-efficient Intelligent Transportation System for Smart Cities

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SURESH CHAVHAN, Automotive Research Center, Vellore Institute of Technolog, Vellore, Tamil Nadu, India, and Federal University of Piauí, Teresina – PI, Brazil
DEEPAK GUPTA, Maharaja Agrasen Institute of Technology, Delhi, India, and Federal University of Piauí, Teresina – PI, Brazil
SARADA PRASAD GOCHHAYAT, Old Dominion University, USA
CHANDANA B. N., Department of Electronics and Electrical Communication Engg., IIT Kharagpur India
ASHISH KHANNA, Maharaja Agrasen Institute of Technology, Delhi, India, and Federal University of Piauí, Teresina – PI, Brazil
K. SHANKAR, Federal University of Piauí, Teresina, Brazil
JOEL J. P. C. RODRIGUES, Senac Faculty of Ceará, Fortaleza – CE, Brazil and Instituto de Telecomunicações, Covilh, Portugal

With the advancement of information and communication technologies (ICTs), there has been high-scale utilization of IoT and adoption of AI in the transportation system to improve the utilization of energy, reduce greenhouse gas (GHG) emissions, increase quality of services, and provide many extensive benefits to the commuters and transportation authorities. In this article, we propose a novel edge-based AI-IoT integrated energy-efficient intelligent transport system for smart cities by using a distributed multi-agent system. An urban area is divided into multiple regions, and each region is sub-divided into a finite number of zones. At each zone an optimal number of RSUs are installed along with the edge computing devices. The MAS deployed at each RSU collects a huge volume of data from the various sensors, devices, and infrastructures. The edge computing device uses the collected raw data from the MAS to process, analyze, and predict. The predicted information will be shared with the neighborhood RSUs, vehicles, and cloud by using MAS with the help of IoT. The predicted information can be used by freight vehicles to maintain smooth and steady movement, which results in reduction in GHG emissions and energy consumption, and finally improves the

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Authors' addresses: S. Chavhan, Automotive Research Center, Vellore Institute of Technolog, Vellore, Tamil Nadu, India, and Federal University of Piauí, Teresina – PI, Brazil; email: suresh.chavhan046@gmail.com, suresh.chavhan@vit.ac.in; D. Gupta and A. Khanna, Maharaja Agrasen Institute of Technology, Delhi, India, and Federal University of Piauí, Teresina – PI, Brazil; emails: {deepakgupta, ashishkhanna}@mait.ac.in; S. P. Gochhayat, Old Dominion University, USA; email: sgochhay@odu.edu; Chandana B. N., Department of Electronics and Telecommunication Eng., SIT Tumkur, India; email: chandanabn65@gmail.com; K. Shankar, Federal University of Piauí, Teresina 64049-550, Brazil; email: drkshankar@ieee.org; J. J. P. C. Rodrigues, Senac Faculty of Ceará, Fortaleza – CE, Brazil, and Instituto de Telecomunicações, Covilh, Portugal; email: joeljr@ieee.org.

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freight vehicles' mileage by reducing traffic congestion in the urban areas. We have exhaustively carried out the simulation results and demonstrated the effectiveness of the proposed system.

CCS Concepts: • **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability;

Additional Key Words and Phrases: Artificial intelligence, Internet of Things, ITS, MAS, edge computing, cloud computing, cyber physical systems

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1 INTRODUCTION

Nowadays, there are many life threats to humanity; one of the major threats is global climate change, that is, an exponential increase of greenhouse gas (GHG) rates into the environment [1–3]. Controlling and reducing the concentration of CO_2 in the environment has become the greatest challenge for humans. The transportation sector in all major cities is one of the main CO_2 contributors. From the current survey, light-duty vehicles (like cars, rickshaws, trucks, etc.) contribute 58%, and medium- and heavy-duty trucks and buses contribute 25% of CO_2 emissions from fossil fuel combustion. The total transportation industry contributes 83% of CO_2 emissions in the air. In addition, the CO_2 emissions from road transport are still exponentially increasing with the increase in the human population and development of industries, especially in metropolitan cities. Hence, it has become a major function to monitor and reduce greenhouse gas emissions from road transport [24–27]. The combination of **artificial intelligence (AI)**, **multiagent system (MAS)**, and **Internet of Things (IoT)**, denoted as A-MIT, is capable of collecting, processing, predicting, and sharing a huge amount of data generated at various devices and infrastructures in urban areas [4, 5, 7, 9, 11, 19, 20]. With the development, advancement, and maturity of **information and communication technologies (ICTs)** and A-MIT, it is essential to analyze the possibility and efficiency of AI-empowered [12, 21–23] IoT-based [14, 17, 21] **intelligent transportation systems (ITSs)** [7, 9, 11, 13, 14, 16]. ITSs are one of the building blocks of a smart city and are closely related to people's day-to-day activities. Most of the countries in the world have been reporting that a lot of cities are facing common issues, which are managing the traffic flow, reducing traffic congestion, reducing the GHG emissions, and so forth [27–29]. Considering the above fact, integrated communication approaches between vehicles, traffic lights, **roadside units (RSUs)**, and the cloud are one of the approaches to address the above-mentioned issues [25–28]. In recent research, many researchers have proposed many algorithms, solutions, and methods for traffic light control [10, 20, 29, 31], traffic smoothing [15–19, 23, 25], and so forth, in order to reduce CO_2 emissions and increase fuel efficiency and vehicle mileage in urban areas [1–3, 24–29, 31]. In the literature, road-transport-based CO_2 emissions will be controlled using many approaches, such as MOBILE, the Comprehensive Modal Emission Model, Emission factors, COPERT, the Motor Vehicle Emission Simulator, and the International Vehicle Emissions model [2–4]. Few works have been carried out to determine vehicle technology and patterns of driving using dynamic traffic simulation models [5, 6], which are realized using TRANSIMS, VISSIM, and INTEGRATION simulation software. This software can be used only for simple traffic conditions' representation; unfortunately, they will not provide the real-time vehicle driving patterns. The authors in [1] discussed the traffic smoothing techniques and showed a result in CO_2 reductions of 10% to 20%. The evolution and advancement of ICTs led to the development of ITSs. The ITS acquires high-quality real-time traffic data [6–10], manages efficient traffic, provides optimal communications, and gives route guidance support services to transport commuters. The traffic data collected from the ITS can be used for estimating the density of greenhouse gas emissions at each location as well as at each vehicle. To the best of our literature knowledge, few researchers have carried out their research on real-time CO_2 emission monitoring using ITS traffic data [11–15]. However, researchers have not concentrated on the communication framework required for the heavy-duty vehicles' accelerating/decelerating, steady movement, preceding vehicles' future state, and so forth. Currently, China contributes 25.4% of the world's greenhouse gas emissions, the United States contributes 17.3%, and India contributes 6.6%.

1.1 Origin of Problem Statement

Emission rates of vehicles depend mainly on the vehicles' traffic characteristics [1–3, 28–31], including vehicles' acceleration and deceleration, traffic speed, vehicles' traffic situation, idling-stop and go-free flow, vehicles' queuing on road, and time headway. Hence, in order to provide sustainable transportation and control greenhouse gas emissions from vehicle traffic, the capability of managing and controlling vehicles' traffic characteristics to reduce emissions needs to be determined. The application of ICTs to transportation is known as ITS. ITS-based freight transportation mostly concentrates on providing safety, mobility management, avoiding accidents/crashing, and so forth on the roadways [16–20]. As a result, there will be a reduction in accidents and efficient mobility management, which result into smooth and steady movements of vehicles on the roadway. Comparing the smooth and steady movement of vehicles with vehicles crawling in slow, stop-and-go traffic, there will be less energy consumption and CO_2 emissions per unit distance. Therefore, the ITS contributes to reducing the GHG emission in the environment, vehicles' mileage improvement, lower energy consumption, and so forth. The research work in this article is inspired by the concept of the connected vehicles and vehicle routings technique, which helps to reduce the effect of traffic congestion by integrating a traffic prediction mechanism for traffic congestion assessment and mitigation [21, 24, 28, 30, 33, 35]. The origin of the proposal is from the following scenario. Let's consider the heavy-duty vehicles that have more than 12 wheels. On the roadway we will encounter situations such as breakdowns, taking turns, and red lights turning on; in all of these situations heavy-duty vehicles put out more energy to start. This results in more emission of CO_2 into the environment and higher energy consumption. These heavy-duty vehicles/trucks contribute at least 25% of the total transportation industry contribution of CO_2 emissions into the air. The main aim of the research work in this article is to reduce this 25% of CO_2 emissions into the air.

1.2 Objectives of the Problem Statement

The main objectives are as follows: (1) division of urban areas into multiple regions and each region sub-divided into a finite number of zones; (2) optimal deployment of RSUs at each critical point (traffic light, turn-taking location, etc.) in every region and zone; (3) MAS- and IoT-based ITS for real-time traffic data collection, analysis, and sharing at each zone in every region; (4) development of **Radial Basis Function Neural Network (RBF-NN)**-based vehicle speed, travel time, and traffic forecasting at each zone in the regions; (5) ITS-based transport vehicles' driving pattern generation (acceleration, deceleration, etc.) and prediction and preceding vehicles' future state and driving pattern prediction; and (6) development of communication framework between vehicles and RSUs: during communication they exchange the following information: speed, roadwork, preceding vehicles, expected clearance time, traffic density, and so forth.

1.3 Contribution and Novelties

Based on the aforementioned discussion, the current research is primarily focused on developing and designing an eco-traffic, speed, and travel time prediction-based ITS for freight vehicles in urban areas. The main contributions and novelties of this article can be outlined as follows:

(1) Propose an artificial intelligence empowered Internet of Things-based eco-traffic, speed, and travel time prediction architecture. The prediction-based intelligent transport system is designed to reduce greenhouse gas emissions and energy consumption.
(2) Build a novel technique based on multiagent system for data collection and edge computing for data analysis in an urban area.
(3) Develop a stochastic queuing model for the freight vehicles' arrival and departure in the coverage area of RSUs.
(4) Build the mathematical model of estimation of freight vehicles' traffic density, speed trajectory, and travel time.
(5) Design an RBF-NN-based freight vehicle traffic density, speed trajectory, and travel time prediction model.
(6) Propose an optimal freight vehicle speed trajectory and estimation of preceding vehicles' travel time and queue in an urban area.
(7) The proposed system is exhaustively tested through simulation. Results are analyzed with varying parameters such as prediction (traffic density, travel time, and speed trajectory), queue length, waiting time, GHG emissions, fuel consumption, and noise pollution during rush hour.

Finally, the above-mentioned contribution results in a reduction in CO_2 and energy consumption, improvement of vehicles' mileage, constant smooth traffic flow, waiting time, and so forth.

The rest of the article is organized as follows. Section 2 presents the proposed AI-empowered IoT-based eco-traffic, speed, and travel time prediction architecture along with the methodology and mathematical model. Section 3 presents the simulation scenario and simulation and performance evaluation of the proposed system. Section 4 draws the conclusions.

2 PROPOSED A-MIT-BASED ECO-TRAFFIC, SPEED, AND TRAVEL TIME PREDICTION ARCHITECTURE

In this proposal, the goal is to design an **eco-traffic, speed, and travel time prediction-based Intelligent Transport System (Eco-TSTTP-ITS)** for freight vehicles in urban areas to reduce GHG emissions and energy consumption. The overall architecture of the proposed system is shown in Figure 1. The architecture consists of five major modules: Distance Estimation, Traffic Reduction, Preceding Vehicles Data Collection, Speed, and Travel Time Prediction. The proposed architecture acquires information from RSUs, **Global Positioning System (GPS)**, **On-Board Diagnostic (OBD)**, Radar, and the **Dedicated Short Range Communication (DSRC)** protocol equipped in the vehicles. All this information will be taken into account by the above-mentioned modules and predict eco-friendly speed, traffic, travel time, distance to critical points, preceding vehicle's future states, time to collision profiles, and so forth, using the RBF-NN. The RBF-NN is used to implement the prediction model using real-time information due to its high accuracy, efficiency, and adaptability. The model predicts in both peak and non-peak-hour traffic in the urban areas. The predicted information, such as vehicle's speed, distance, expected clearance time, travel time, traffic density, and expected green light time, will be sent to the vehicle's driver through the **Human-Machine Interface (HMI)** module. Using this predicted information, the driver will accelerate/decelerate and maintain the speed.

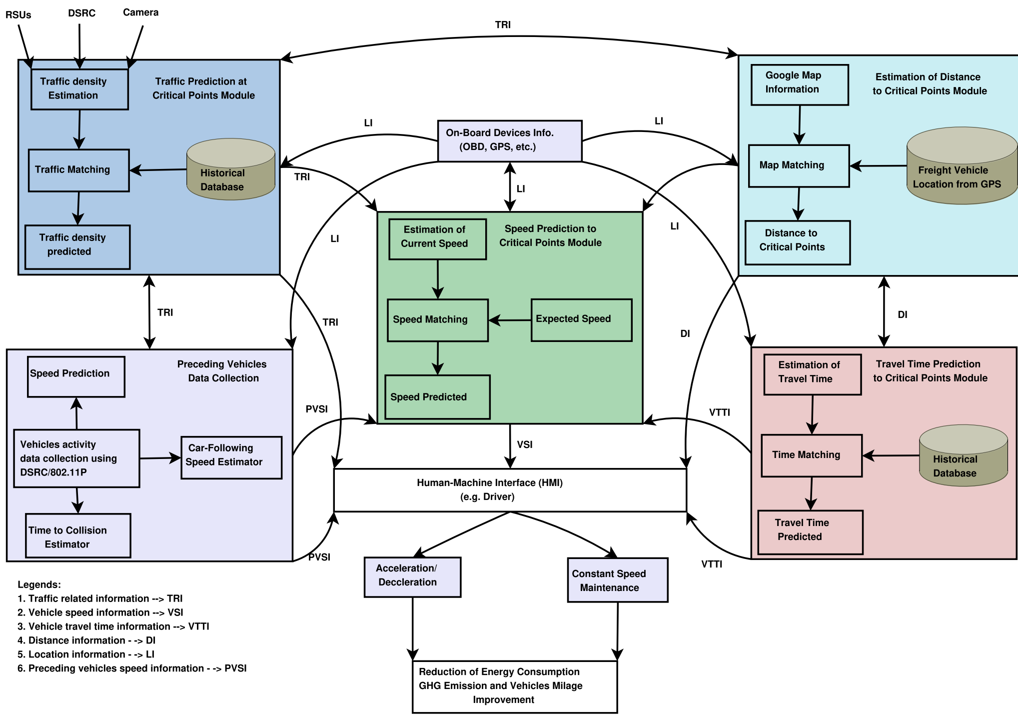


Fig. 1. Proposed an A-MIT-based eco-traffic, speed, and travel time prediction architecture.

2.1 Methodology

In this proposal, an Eco-Traffic, Speed, and Travel Time Prediction is done at critical points/places (like traffic lights, taking turns, etc.) based on observed real-time and historical traffic pattern information. A multiagent system is deployed at each critical point's RSUs and freight vehicles. The MAS-based ITS collects; edge computing devices analyze; AI predicts the traffic, speed, travel time, and preceding vehicles' future states and speed; and IoT is used to share this information. The DSRC protocol is used for sharing the current and preceding vehicles' speed, future states, incidents, traffic-related information, and so forth. IoT along with the DSRC protocol is used in MAS and ITS for efficient collection, sharing, and management of traffic and coordination among freight vehicles. Efficient traffic management leads to smooth and steady movement of freight vehicles, which reduces CO_2 and energy consumption in urban areas.

2.2 Layers of A-MIT-based ECO-TSTTP-ITS

The complete A-MIT-based ECO-TSTTP-ITS architecture is shown in Figure 1, which is composed of four different layers: (1) Infrastructure, (2) Network Layer, (3) Service, and (4) Application, as shown in Figure 2. In this figure, each layer's information will flow only through **service access points (SAPs)**. The SAPs act as a port or door for the information flow from Layer + i to Layer i and vice versa.

(1) Infrastructure Layer: It includes all types of devices, such as sensors, radars, OBD, GPS, RSUs, and vehicles. MASs are deployed in these devices to collect the data and provide it to the edge computing device. The edge computing device analyzes the collected data and refines it. The refined data is recorded and given to the network layer for sharing.

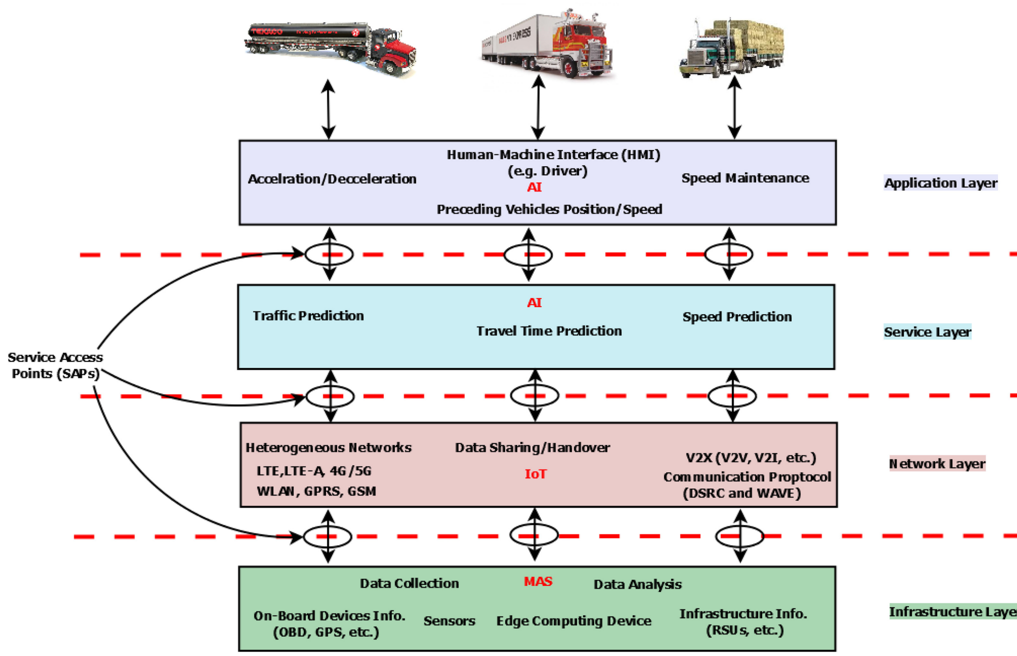


Fig. 2. Layers of an A-MIT-based ECO-TSTTP-ITS.

(2) Network Layer: This layer is mainly responsible to provide the seamless connectivity using IoT communication technologies, such as LTE, 4G, 5G, and WLAN. Also, the DSRC communication protocol is required for V2X data sharing.
(3) Service Layer: It's mainly responsible for AI-based prediction and service provision. It consists of three sub-modules: (i) Traffic Prediction, (ii) Travel Time Prediction, and (iii) Speed Trajectory Prediction. In this layer, the RBF-NN is used for predicting the above-mentioned information. This predicted information is shared with the neighbor vehicles and nearby RSUs and stored in the cloud.
(4) Application Layer: This layer receives the predicted information; depending upon this data the freight vehicle either accelerates/decelerates. The distanced freight vehicle will maintain the predicted speed till it reaches the critical point from where the information was received.

2.3 MAS-based Data Collection and Analysis

MASs are deployed in vehicles and RSUs. At each intersection, an RSU is installed with an agent in it to collect real-time traffic and vehicle speed and dynamically control traffic lights (both vehicles and pedestrians) in all directions as shown in Figure 3. As we know, surveillance cameras are deployed on each road for detecting pedestrians' and vehicles' queue lengths. An agent deployed in the RSU collects the local traffic data from the surveillance cameras and stores it in the local database. In addition, agents also collect data from the neighborhood RSUs (like traffic density, speed of vehicles, clearance time, etc.) and vehicles (speed profile, destination, travel time, etc.) and store it in the local database. Depending upon the database and historical database, the edge computing device estimates the optimal control actions (like traffic light controlling, etc.) and refines and analyzes data sharing (like expected speed the vehicles need to maintain, expected clearance time, etc.).

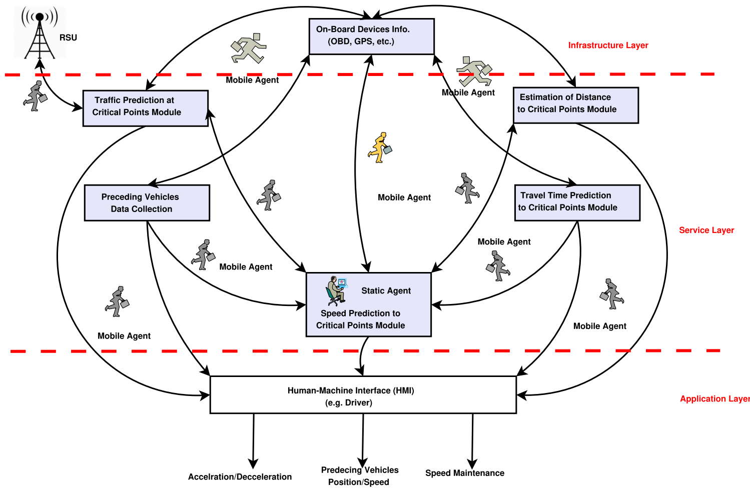


Fig. 3. MAS-based traffic data collection and analysis.

2.4 Stochastic Queuing Model for the Freight Vehicles in the Coverage Area of RSU

We have stochastically modeled the queue length of vehicles on each direction of the roads and intersections. Figure 4 shows the stochastic queuing model of the vehicles entering into the coverage area of RSUs and maintaining the speed, i.e., acceleration and deceleration. We have assumed that during acceleration it will have n number of states and similarly for deceleration will have m number of states. In Figure 4, the vehicle entering can accelerate or decelerate; suppose the vehicle is accelerating: the next state may be acceleration or deceleration depending upon the information sent by the RSU. In the figure it is also shown that there is a transition from RSU 1->RSU 2, RSU 2->RSU 3, . . . , RSU k-1->RSU k.

The vehicle enters into the coverage area of the RSU whether or not the vehicle will join the queue. Table 1 shows the Mathematical Symbols and Their Meanings used for developing the analytical model. The departure process of the freight vehicle in the coverage area R of the RSU is more stable as compared to the Poisson arrival process of freight vehicles. The departure rate of freight vehicles from the coverage area of the RSU is constant. μ indicates departure rate, λ represents arrival rate, and Δv_h is the freight vehicle spacing headway; these were estimated by using the historical data. Each RSU contains 2-M/M/m queues with state transition from one queue to another queue as shown in Figure 4. Steady state probabilities of the freight vehicles' acceleration phase are given as

$$p_m^a = \begin{cases} \frac{p_0 (np)^n}{n!}, & m \leq n \\ \frac{p_0 n^n p^m}{n!}, & m > n, \end{cases} \tag{1}$$

where ρ is the utilization factor and is given as

$$\rho = \frac{\lambda}{n\mu} < 1. \tag{2}$$

p_0 is calculated by using the above expression and the condition $\sum_{n=0}^{\infty} p_n = 1$. We obtain

$$p_0 = \left[1 + \sum_{m=1}^{n-1} \frac{(n\rho)^m}{m!} + \sum_{m=n}^{\infty} \frac{(n\rho)^m}{m!} . \frac{1}{n^m - m} \right]^{-1}. \tag{3}$$

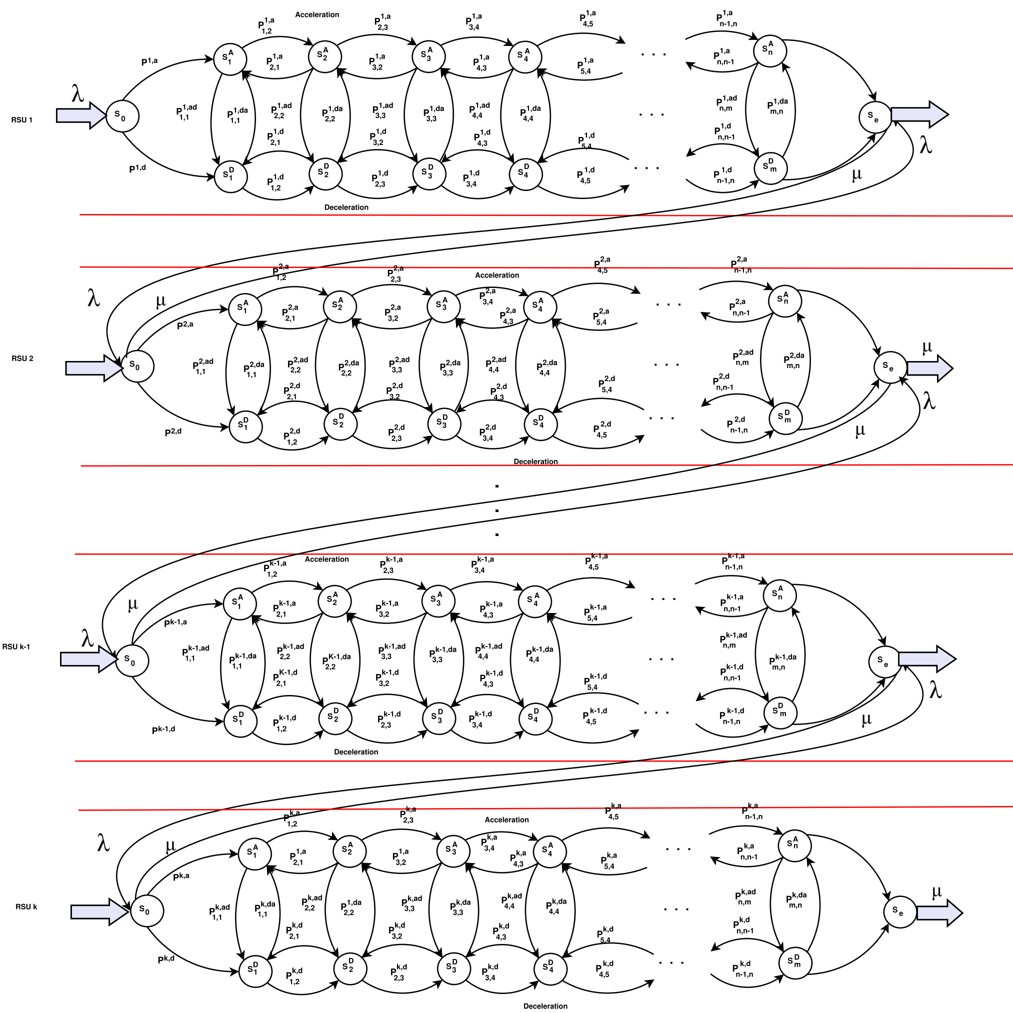


Fig. 4. Stochastic queuing model for the freight vehicles' arrival and departure in the coverage area of RSUs.

The probability that vehicles will wait in a queue is given as

$$P(Queuing) = P_Q^a = \sum_{m=n}^{\infty} p_m \tag{4}$$

$$P_Q^a = \sum_{m=n}^{\infty} \frac{p_0 n^n \rho^m}{n!} = \frac{p_0 (n\rho)^n}{n!} \sum_{m=n}^{\infty} \rho^{m-n}. \tag{5}$$

The expected number of freight vehicles waiting in a queue on the road is given by

$$N_Q^{a,v} = \sum_{m=0}^{\infty} m p_{n+m}. \tag{6}$$

Table 1. Mathematical Symbols and Their Meanings

Symbols	Meaning
μ	Departure rate of vehicles
λ	Arrival rate of vehicles
Δv_h	Freight vehicle spacing headway
ρ	Vehicle utilization factor
p_m^a	Steady state probability of the freight vehicles' acceleration phase
P_Q	Probability freight vehicles are in queue
N_Q	Expected number of freight vehicles waiting in a queue
W^a	Average waiting time of freight vehicles in a queue
Q_L	Queue length of freight vehicles waiting in queue
$T^{pv}(t)$	Travel time of preceding vehicles
$T_a \& T_p$	Actual travel time and preceding vehicle's reaching the queue end location time step
R	Coverage area of RSU
$D^{v,j}(t)$	Freight vehicles traffic density in the jth RSU at time t
m	Number of vehicles available in the coverage area of RSU
S	Freight vehicle speed trajectory sinusoidal profile
τ	Jerk, acceleration, and deceleration profiles

The above equation can be re-written as

$$N_Q^{a,v} = \sum_{m=0}^{\infty} n p_0 \frac{n^n \rho^{m+n}}{n!} = \frac{p_0 (n\rho)^n)}{n!} \sum_{m=0}^{\infty} m\rho^m \tag{7}$$

$$N_Q^{a,v} = P_Q^a \frac{\rho}{1-\rho}. \tag{8}$$

From Little's Theorem, the average waiting time W of a freight vehicle in a queue is given as

$$W^a = \frac{N_Q^{a,v}}{\lambda} = \frac{\rho P_Q^a}{\lambda(1-\rho)}. \tag{9}$$

Similarly, the freight vehicles' deceleration phase steady state probability is given as p_n^d, P_Q^d is the probability that the freight vehicles will wait in a queue, $N_Q^{a,v}$ represents the expected number of freight vehicles waiting in a queue, and W^a is the average waiting time of freight vehicles in a queue.

Based on the freight vehicles' traffic density and queue spacing, the queue length could be estimated as follows:

$$Q_L = \left(N_Q^{a,v} + N_Q^{d,v}\right) \times \Delta v_h \times \left(P_Q^a + P_Q^a\right). \tag{10}$$

The travel time of the preceding vehicles is estimated as

$$T^{pv}(t) = \frac{D_a - V_c - Q_L}{W^a + W^d + T_a - T_p}, \tag{11}$$

where T_a and T_p are the actual travel time and preceding vehicle's reaching the queue end location time step, respectively; D_a and V_c represent actual distance from the vehicle and current distance to the actual stop, respectively.

2.5 Freight Vehicle Traffic Estimation and Prediction

Each RSU deployed at a critical point provides seamless communication connectivity in its coverage area. In the coverage area R, every vehicle maintains the same speed S, distance between vehicles is also same x and different arrival rates (λ) of vehicles in it. The observed traffic density at time t in the coverage area R of RSU 1 and each freight vehicle occupying length Δv is given as

$$\Delta^{v,1} = \frac{\lambda_1 R}{\Delta v S^1}. \tag{12}$$

In general, the freight vehicles' traffic density in the jth RSU at time t is given as

$$D^{v,j}(t) = \frac{\lambda_j R}{\Delta v S^j}. \tag{13}$$

The arrival of freight vehicles in the coverage area of the RSU is a Poisson point process with density δ. The probability of m number of vehicles available in the coverage area R of RSU j is given as

$$p^{v,j}(m, R) = \frac{(\delta R)^m}{m!}. \tag{14}$$

The freight vehicles' traffic density prediction in RSU j at time t is estimated using the observed, unexpected, and historical traffic density, given as

$$P^j(t) = \frac{\lambda_j R}{\Delta v S^j} + \frac{(\delta R)^m}{m!} + max(H^{v,j}(t) - [D^{v,j(t)} + p^{v,j}(m, j)], 0), \tag{15}$$

where $H^{v,j}(t)$ is the historical freight vehicles' traffic density in RSU j at time t.

2.6 Freight Vehicle Speed Trajectory, Distance, and Travel Time Estimation

Consider S_c to be the current speed and S_τ to be the speed limit of the freight vehicles in the coverage area R of RSU.

The vehicles' speed trajectory profile is sinusoidal and is given as follows:

$$S = \begin{cases} \frac{S_\tau + S_c}{2} - \frac{S_\tau - S_c}{2} Cos(\tau t) \; t\epsilon[0, \frac{\pi}{\tau}] \\ S_\tau \; t\epsilon[\frac{\pi}{t}, \infty] \end{cases},$$

where τ indicates jerk, acceleration, and deceleration profiles. Most of the commuters do not like the jerks on the road; therefore, we assume maximum ($J_{max} = 10m/s^3$) and minimum acceleration ($A_{min} = 2.5m/s^2$). Hence, the value of m is selected in such a way that the commuters should feel comfortable during traveling on the road:

$$\tau = min\left(\frac{2A_{min}}{S_\tau - S_c}, \sqrt{\frac{2J_{max}}{S_\tau - S_c}}\right). \tag{16}$$

The acceleration time period is π/τ, which is the half sinusoidal cycle. The distance traveled by the vehicle when accelerating is applied to the freight vehicles:

$$D_A = \int_0^{\pi/\tau} \left[\frac{S_\tau + S_c}{2} - \frac{S_\tau - S_c}{2} Cos(\tau t)\right] dt. \tag{17}$$

The freight vehicles reach the intersection by keeping the speed trajectory limit to S_τ. The minimum travel time required for the freight vehicles to cross the intersection is given as

$$TT_{min} = \frac{\pi}{\tau} + D - D_A. \tag{18}$$

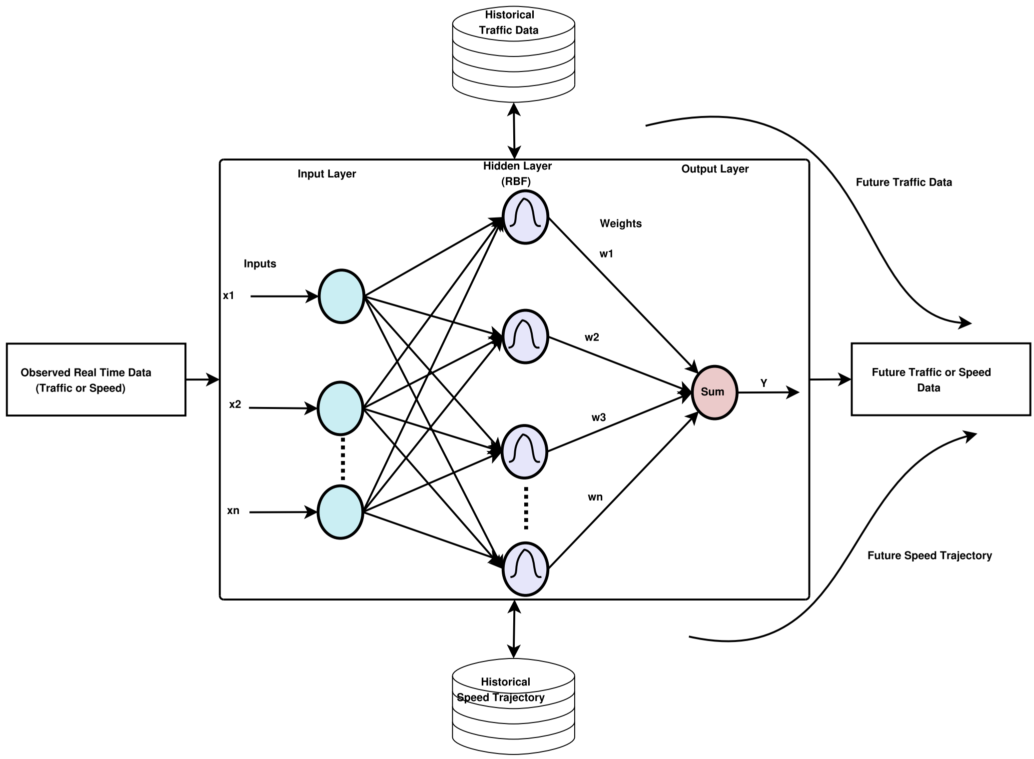


Fig. 5. Freight vehicles' traffic density and speed trajectory prediction based on RBF-NN model.

2.7 Freight Vehicle Traffic Density and Speed Trajectory Prediction Based on RBF-NN Models

To the best of our knowledge, most of the researchers have worked on various prediction approaches based on time series to predict the speed of vehicles on the segment or link level and also under the scenario of highway. None of these approaches have discussed the freight vehicles' speed trajectory prediction for microscopic traffic density scenarios. We implement the prediction model using RBF-NN with observed and historical speed trajectory of the freight vehicles. The RBF-NN prediction model consists of a feed-forward neural network; one hidden layer consists of the radial transfer function as shown in Figure 5. The model takes observed and historical freight vehicles' speed trajectory data and produces the output predicted freight vehicles' speed trajectory. In this prediction model, we used activation function as Gaussian, given as

$$\rho_i(k) = e^{\left[-(\bar{k}-\gamma_i)^{\tau} \sum_j^{-1}(\bar{k}-\gamma_i)\right]} \tag{19}$$

$$y_x(k) = \sum_j^{L} w_{kj}\rho_i(k) + d_{kj}, \tag{20}$$

where $\rho_i(k)$ is node j's activation function; $\bar{k}$ is node j's input vector; w_{kj} is the weight assigned to node j; d_{kj} is the constant bias; γ_i and $\sum_j$ are the ith Gaussian function's mean vector and covariance matrix, respectively—they indicate the activation function's center and shape. Finally, each node's output at the RBF-NN's output layer is computed. The output layer's output is a linear combination of the hidden nodes. The RBF-NN prediction model

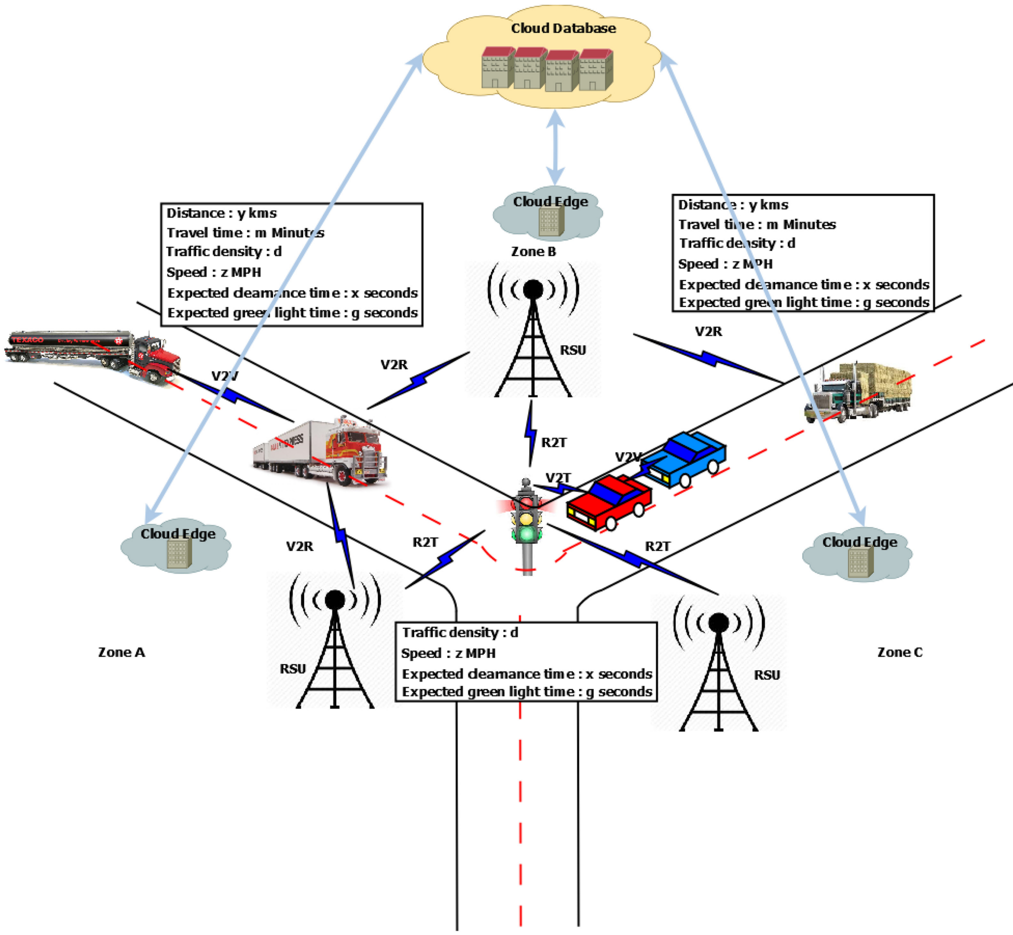


Fig. 6. Scenario of hierarchical communication with information sharing between entities.

shows more robustness to adversarial noise and easier generalization compared to MLP-NN. The RBF-NN model consists of two stages: (1) In the training process, the basis function's parameters are used to model the unconditional data density. (2) The generalized pseudo inverse of Moore-Penrose is used to determine the weights between the (output and hidden) layers. It reduces the problems in the traditional algorithms like learning rates, local minima, stopping criterion, and number of epochs. The RBF-NN prediction model is used to forecast the real-time freight vehicles' speed trajectory in urban areas because of the following advantages: (1) less training time, (2) high accuracy of prediction, and (iii) high ability of generalization.

2.8 Optimal Freight Vehicle Speed Trajectory

Figure 6 shows the flow of information from the traffic light situated at the intersection to the nearby RUSs and vehicles on all the roads. Also shown is the flow of information through different communication technologies, i.e., V2V, V2I, cloud to cloud, and RSUs to cloud. The freight vehicle that has approached the intersection initiates the communication with the traffic light as well as with the RSUs. The distributed multiagent situated in the traffic light and RSUs analyzes the observed real-time traffic data and speed trajectory along with the historical traffic data and speed trajectory. Using the RBF-NN, which predicts the speed trajectory, expected clearance time, expected time of green light to switch on, and so forth, information is communicated with the nearby vehicles as well as with the RSUs. The received vehicles will propagate the received information to the nearby vehicles using V2V communication technology. The RSUs will send the estimated information to all the vehicles that are in its coverage area; each vehicle will get different information depending upon their location and traffic density on the road it is traveling. The vehicles' queue length is estimated using the queuing model as shown in Figure 4. With the estimated preceding queuing length along with the historical information, we have formulated for freight vehicles an optimal speed trajectory that avoids and reduces unnecessary acceleration, deceleration, waiting, and so forth, on the roads.

Gipp's model is used to formulate freight vehicles' optimal speed trajectory that is highly energy efficient and safe, given as follows:

$$S^{opt}(t+\delta) = min\left\{S_m(t) + 2.5A_m\delta\left(1 - \frac{S_m(t)}{S_m^d}\right), b_m\delta + \sqrt{b_m^2\delta^2 - b_m\left[2(x_{n-1}(t) - v_{m-1} - x_m(t)) - S_m(t)\delta - S_{m-1}(t)^2/b\right)\right]}. \tag{21}$$

where δ represents reaction time; $S_n(t)$ and $S_{n-1}(t)$ indicate the speed profile of the behind vehicle n and preceding vehicle $n-1$, respectively; S_m^d is the nth vehicle's desired speed; A_m is the maximum acceleration of the nth vehicle; and b_n and b are the nth vehicle's most severe braking and expected leading vehicles' maximum deceleration, respectively.

3 RESULTS AND DISCUSSION

In this section, we present the real-time dataset, simulation scenario, and simulated results discussion.

3.1 Real-time Dataset

The proposed prediction system's performance is evaluated using the **Next Generation Simulation (NGSIM)** dataset [38], which is the detailed freight vehicles' trajectory data on Peachtree Street in Atlanta, Georgia. The dataset is provided with precise location of each freight vehicle within the study area every one-tenth of a second, which results in vehicles' detailed spatial and temporal information along with the positions and locations of lanes with the other vehicles as well as information of the traffic light from 9 am to 11:59 am, 1 to 3 pm, and 4 to 5 pm on March 23, 2020. The collected data is segregated into portions: (1) training data: 70% of the real-time data randomly selected and (2) testing data: 30% of the real-time data randomly selected. In order to get a reliable and more accurate prediction of freight vehicles' traffic density, speed trajectory, and travel time, we have extracted the following information from the dataset: vehicle ID, speed profile of each vehicle for every second, acceleration, deceleration, lane id, direction, preceding and following vehicles, origin and destination of vehicles, intersection id, and vehicle space and time headway. The real-time traffic data available in the NGSIM database are raw data and in order to use these data we have followed subsequent steps:

(1) Acquiring data: We acquired traffic flow data of 50 consecutive locations of the US 101 Highway for 30 days from the NGSIM database. The aforementioned 30 days of data are from June 1, 2015, to July 1, 2015, and data granularity considered is 5 minutes. We have every 5 minutes of traffic flow of 50 network points for 30 days.
(2) Cleaning acquired data: We observed and checked the raw data and identified a few temporal points, where there is no information about traffic flow and density. For example, in the raw data we have traffic flow for a particular day at time 12:35 and 12:45, but no data at time

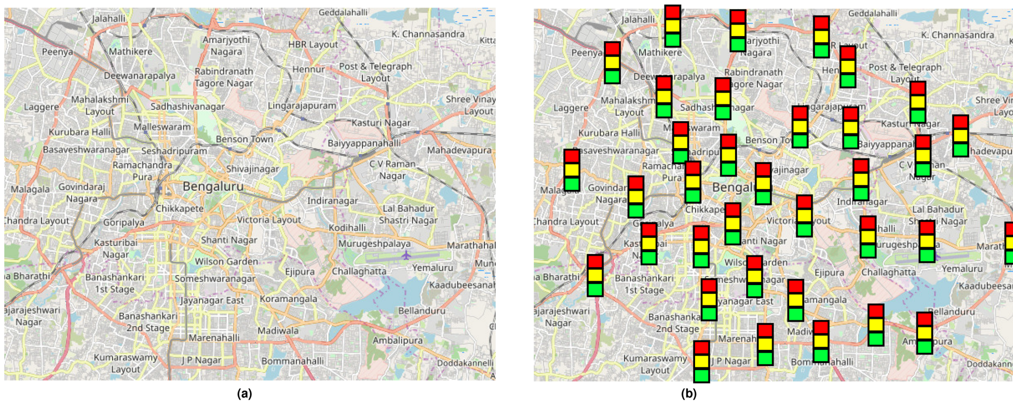


Fig. 7. (a) OpenStreetMap of Bangalore metropolitan area. (b) Real-time deployment of traffic light controller.

12:40. Therefore, in such cases we calculate the mean values of data of 12:35 and 12:45, and it is considered for 12:40.

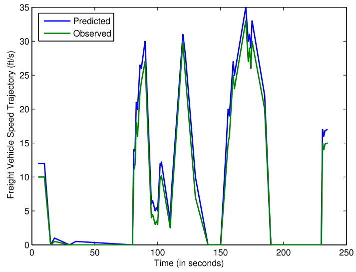
(3) Normalize cleaned data: Here, we converted the traffic flow and time to values in [1,0). In order to carry out this, we divide all values by their possible maximum values, i.e., 1 to 7 for all days (1 is assigned to Sunday, 2 is assigned to Monday, etc.), and 30 (1 is assigned to (00:00, 00:30) and so on) to the time of the day. This normalized dataset is used for training and testing. Prior to the training, the dataset is divided into three subsets as follows: (i) training set: 60% of dataset is used for training, (ii) cross-validation set: 20% of dataset is used for testing the training process against over-fitting, and (iii) testing set: 20% of dataset is used for evaluating the prediction performance.

3.2 Simulation Scenario

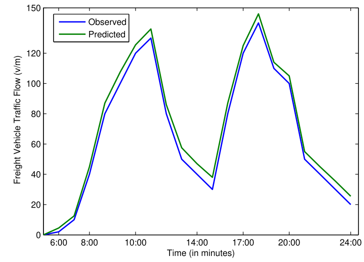
We simulate the proposed eco-energy-efficient intelligent transport system in the **Simulation of Urban Mobility (SUMO)** [39]. The SUMO models the microscopic traffic conditions and has a very well-designed API for controlling the status of traffic lights through online interaction. We export the map of a Bangalore metropolitan area, Karnataka, India, using **OpenStreetMap (OSM)** [40] as shown in Figures 7(a) and 7(b), where the Bangalore metro area is converted into SUMO compliant network topology with a traffic light at every intersection. We deployed the distributed multiagent system at each intersection's traffic light, vehicles, and RSUs. In this scenario, we used real-time traffic data, which are obtained from the NGSIM.

3.3 RBF-NN-based Freight Vehicle Density, Speed, and Travel Time Prediction Model

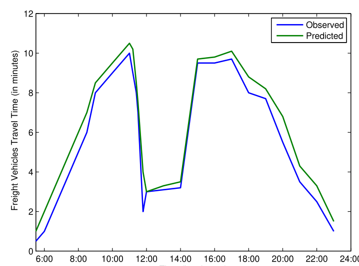
The RBF-NN contains three layers: (1) input layer, (2) hidden Layer, and (3) output layer. In this model, we used Gaussian function as a basis function in the hidden layer to account for the nonlinearity. There are two parameters available in Gaussian function, i.e., center (γ_i) and peak width (sum_i). The successful prediction of freight vehicles' traffic density, speed trajectory, and travel time is based on RBF-NN [41] to find suitable centers for each Gaussian function. The RBF-NN forecasting model minimizes the error by adjusting the weighting factor w for each neuron along with the bias coefficient. In the model, we have considered three driving scenarios, with 15, 10, and 5 neurons, respectively, in the hidden layer. In Scenario I, the RBF-NN 15 by 3 is both calibrated center and hidden layer's weights with 3 by 1 bias vector and 15 is a peak width of a vector. Scenario II, 10 by 3 is both calibrated center and hidden layer's weights with 10 by 1 and 3 by 1 are peak



(a) RBF-NN based freight vehicles speed trajectory prediction



(b) RBF-NN based freight vehicle traffic flow prediction



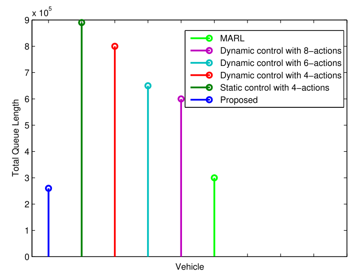
(c) RBF-NN based freight vehicles travel time prediction

Fig. 8. Results: RBF-NN-based prediction of real-time freight vehicles' speed trajectory, traffic flow, and travel time.

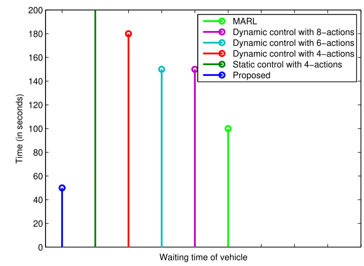
width and bias, respectively. Scenario III, 5 by 3 is both calibrated center and hidden layer's weights with 5 by 1 and 3 by 1 are peak width and bias, respectively. Based on the above driving scenarios, every 3 seconds the short-term vehicle speed trajectory, traffic density, and travel time prediction are generated. Figures 8(a), 8(b), and 8(c) show the RBF-NN-based prediction of freight vehicles' speed, traffic density, and travel time based on the observed and historical data, which is more reliable and accurate.

3.4 Performance Evaluation of the Developed System

In this section, we evaluate the proposed system's efficiency and compare with the existing solutions, that is, (1) Static control: four actions (Static 4), (b) Dynamic control: four actions (Dynamic 4), (c) Dynamic control: six actions (Dynamic 6), (d) Dynamic control: eight actions (Dynamic 8), and (e) **Multiagent Q-Learning algorithm (MARL)**. The existing solutions (a) to (d) assume that sensors detect the freight vehicles and their control. Figure 9(a) shows the freight vehicles' cumulated queue length during rush hour. During red lights, the cumulated queue length is the total number of vehicles that are waiting at the intersection. In the figure we have compared all existing solutions with the proposed system; it can be seen that the proposed system reduces the queuing delay at the intersection. This is due to the communication approach that is periodically sending the vehicle density information at intersections to the vehicles that are far from it. Therefore, the far-away vehicles maintain the suggested speed by the agent that is already deployed at each intersection's RSU. Using SUMO's GUI, the simulation shows the smooth and constant flow of traffic. Figure 9(b) shows the rush-hour freight vehicles' waiting time at the intersections. The result shows that the proposed system's waiting time is much less as compared with the existing solutions. This is because of continuous communication establishment between intersections

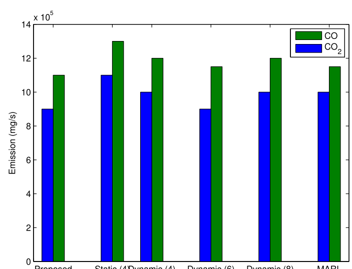


(a) Freight vehicles cumulated queue lengths during rush hour

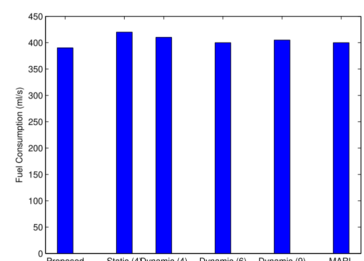


(b) Freight vehicles total waiting time during rush hour

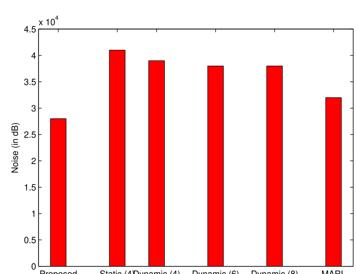
Fig. 9. Freight vehicles' cumulated queue lengths and waiting time during rush hour.



(a) Freight vehicles CO & CO_2 Emission during rush hour



(b) Freight Vehicles Fuel Consumption during rush hour



(c) Freight vehicles noise pollution during rush hour

Fig. 10. Freight vehicles' GHG emissions, fuel consumption, and noise pollution during rush hour.

and vehicles so that the vehicles have maintained constant speed; by the time the vehicles reach the intersection there will be much less or no waiting time. Due to the seamless connectivity and sharing of traffic-related information from intersections to the vehicles that are in the coverage area of RSUs, the repeated starting and stopping of vehicles is avoided or reduced. This results in reduction of greenhouse gas emissions (CO & CO_2), fuel consumption, and noise pollution and improves the freight vehicles' mileage, as shown in Figures 10(a), 10(b), and 10(c). As it is clearly shown, the proposed system outperforms as compared to existing solutions.

4 CONCLUSIONS

The proposed AI-empowered IoT-based energy-efficient ITS reduced GHG emissions, energy consumption, queue length, waiting, time and noise pollution in the environment for smart cities. This has been achieved by using the RBF-NN-, IoT-, and MAS-based real-time data collection, analysis, prediction, and sharing with the DSRC-IEEE 802.11p communication standard protocol for V2X. In addition, the proposed ITS system estimated the accurate clearance time, preceding vehicles' current and future states, and speed that freight vehicles have to maintain in order to reduce the queue length and waiting time. In addition, the proposed system improved the vehicles' mileage, travel time, and driving pattern and avoided accidents.

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