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SMART Emergency Vehicle Management at Signalized Intersection using Machine Learning

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Abstract

Objective: Primary objective of the article is to develop a machine-learning-based pre-emptive traffic signal controller to ensure the free flow of an emergency vehicle across the signalized intersection. **Method**: Pre-emptive signal control system involves various functional modules such as emergency vehicle notification, traffic volume estimation, green time prediction, and signal control. The current study is focused on green time prediction based on traffic composition and volume. The study is presented in two folds; identify a suitable machine learning model to predict the green time and use the selected model to design the proposed system. The results obtained from the proposed system are compared against a non-pre-emptive controller. **Findings**: The Convolution Neural Network (CNN) is found to be the best suitable algorithm for green time prediction. The green time prediction module shares a pivotal role in the system as more/less green time prediction can waste the green time or block the free flow of emergency vehicles. Thus, the accuracy of green time prediction has significance in the system and CNN showed a 96% R2-score. Delay for an emergency vehicle is 86 seconds in a conventional non-pre-emptive controller and it is 8 seconds in the case of proposed system. **Novelty**: Green time prediction under heterogeneous traffic conditions is a challenge. Analytical models are widely used to estimate the green time as per existing research works concerned with emergency vehicle management. However, machine learning models are also in use, but deep learning models are applied rarely, and CNN is applied in current work.

Keywords: Signal preemption; edge computing; machine learning; signalized intersection; emergency management

1 Introduction

Creating a free-flow pathway for emergency vehicles is an emerging area of research in recent decades[(1)]. It is essential to prioritize emergency vehicles at signalized intersections to ensure safety. Emergency vehicles are special-purpose vehicles including ambulances and fire engines, serving in a crucial situation to mitigate property loss and life threats. The standards concerned with emergency services have been set by the nations. An eight-minute target has been set for an ambulance to reach the hospital in case of highly critical medical emergencies as per the National Health Service of England. As per the report by Singapore Civil Defence Force, 88.9% of medical emergency cases were attended within 11 minutes. Most nations including India are rising the demand for lessening the period of emergency rescue. However, the traffic volume is expanding gradually all over the world. A statistical report from the U.S department of transportation clearly showed a significant increase in traffic volume in U.S in urban localities during the year 2020. China and India are also heading towards heavy traffic volume due to the increased use of private vehicles.

The traffic volume is continuously rising whereas the road infrastructure is limited. The financial and other resource limitations impede road expansion, and it leads to congestion on roads. However, signalized intersections are the primary locations of congestion in a road network. The traffic at the signalized intersection is managed by varying signal lengths based on traffic demand and is optimized to mitigate the delay and distribution as well. Different solutions are proposed by various authors across the countries; rule-based[(2)], reinforcement-based[(3)] [(4)] [(5)], and IoT-based[(6)] smart-controller are some of the recent works, and various available solutions are summarized in[(7)]. The congestion always hinders the speed of traffic movement and hence the emergency vehicle as well. In addition, the emergency vehicle has to stop, if it enters the intersection during the red phase and wait for the green and this leads to extended travel time from source to destination. Thus, there is a necessity to prioritize the emergency vehicle at the intersections to provide a freeway along its route. Researchers and experts are working in this direction and proposed various solutions to tackle the issue. The current article studies the existing emergency vehicle management systems and attempts to propose a machine learning-based signal controller to manage an emergency vehicle at a signalized intersection with a higher priority. The proposed solution aims at eliminating the waiting or even deceleration at the intersection.

The emergency vehicle stuck at the signalized intersection will not be able to cross the intersection easily even though it is permitted to move against the normal signal operations as the long queue of normal vehicles is blocking it. The green signal lengths are varied as per traffic demand/flow on approaching roads, but the current green active phase must be pre-empted to provision the freeway for the emergency vehicle so that the emergency vehicle reaches a destination without additional delay. A variety of technologies are involved in the implementation of emergency vehicle management and pre-emption system[(8)].

An emergency vehicle pre-emption module[(9)] was implemented for heterogeneous traffic conditions and the results are presented through VISSIM simulation. A Petri Net model is applied to study the pre-emption signal controller for emergency vehicles[(10)] and the pre-emptive systems were found to be efficient in reducing the delay for an emergency vehicle. An algorithm to schedule the green time for an emergency vehicle by pre-empting the current phase to reduce the delay is presented via an analytical model in[(11)], while, the hardware support essential for implementing priority-based phase allocation for an emergency vehicle is presented in[(12)] using advanced electronic technology. A dynamic[(13)] and autonomous[(14)] pre-emptive signal controller proved their significance in reducing the travel delay of an emergency vehicle.

Communication plays a vital role in smart-mobility implementation. various communication frameworks are in practice such as Vehicle-to-Infrastructure (V2I), Vehicle-to-Vehicle (V2V), Infrastructure-to-Infrastructure (I2I), and Vehicle-to-Everything (V2X). A deep empirical study is presented in[(15)] to explore the contribution of the V2I framework in supporting efficient and safe mobility. Hence, V2I[(16)] and (V2X)[(17)] communication technology is used to design a novel queue discharge technique to provision immediate exit for an emergency vehicle at an intersection. While[(18)] used connected traffic data to design the signal controller for multiple intersections which coordinate with each other to provide green waves to emergency vehicles. A route-based analytical model of traffic signal pre-emption for an emergency vehicle is presented in[(19)]. Whereas, the authors in[(20)] have presented a route-based signal pre-emption system for emergency vehicle exit at a signalized intersection using Intelligent Transportation System (ITS) infrastructure in smart cities. Along with signal prioritization, it is essential to choose the optimal route of travel while attending the emergency calls which is addressed in[(21)].

The two important factors noticed from the literature are; the machine learning is rarely applied in this area and the existing solutions are focused on uniform traffic conditions rather than the heterogeneous traffic. With this view, the primary objective of the article is to develop a machine learning-based model suitable for heterogenous traffic conditions and ensure the free flow of emergency vehicles across the signalized intersection. A theoretical framework of dedicated hardware setup necessary to implement the proposed solution is depicted in Figure 1. The overall system architecture with computation, communication, and storage is laid in four layers including data, hardware, interface, and application. The data plays a vital role in fostering intelligence in the proposed system. The varied information concerning traffic at intersections is exemplified in the data layer. The Signal Controller (SC), Road-Side-Unit (RSU), and On-Board-Unit (OBU) are the important components of the hardware layer;

SC: It is an exclusive device installed at an intersection that activates the corresponding signals with estimated timings.

OBU: It is a special board designed with microcontrollers to establish communication between vehicles and infrastructure (V2I). The dedicated short-range communication and wireless technologies are being used to design OBU. The emergency vehicles are installed with these boards along with GPS devices and can communicate to RSU through 802.11p and V2X interface modules.

RSU: The entire system operations are performed at RSU which is deployed on-site at an intersection. The current signal plans including cycle length, signal phase, green splits, and events detected (if any) are broadcasted at regular intervals of times through the 802.11p interface. An application like smart assistance and emergency management can make use of this information and the OBU in an emergency vehicle can receive this information and act accordingly (re-routing). Whereas the OBU broadcasts its information to RSU through the V2I interface so that the RSU can take an instant decision of prioritizing emergency vehicles at signalized intersections concerning traffic signal activation.

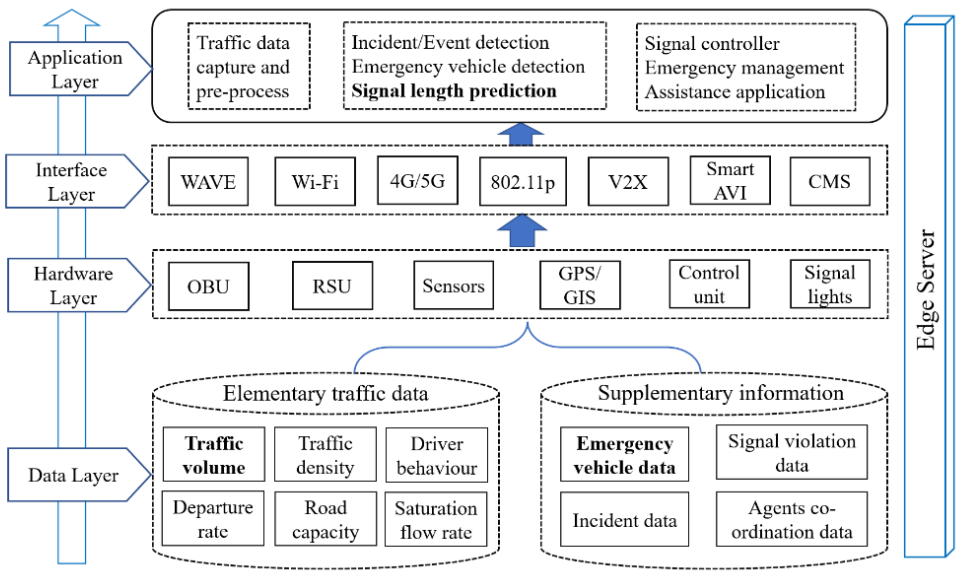

Fig 1. Pre-emptive traffic signal control system architecture

The additional hardware facilities required are GPS/GPRS devices, signal lights, and traditional sensors like loop detectors and cameras. The data, OBU, RSU, and applications are controlled and coordinated through the interface layer. Finally, the application layer presents various software modules developed to accomplish a dedicated task. The data captured through various sensors are moved to the edge server for further processing. The traffic data 'storage', 'processing' and 'computation' is carried over an edge server to reduce the communication overhead that is experienced with cloud servers.

The flow of the remaining sections is as follows; the operation strategy of the proposed solution is described in the next section along with the machine learning model and the data used. The results obtained through simulation are discussed in section 3. Finally, the paper concludes with the core implications of the proposed solution.

2 Methodology

It is more likely to have more than one emergency vehicle entering the intersection from more than one direction at any point in time. However, in the current article, for simplification, it is assumed that an emergency vehicle arrives in any one direction at any point in time. With this assumption the probable scenarios of emergency vehicle entry into the intersection are:

Case-1: Emergency vehicle arrival in the direction of the current green phase.

Case-2: Emergency vehicle arrival at a phase other than the current green active phase.

The Case-1 is addressed through green extension. Whereas case-2 is addressed through red truncation. Further, there are two ways of managing case-2; Red truncation for the emergency phase on-arrival or before-arrival of an emergency vehicle at the intersection.

2.1 Significance of before-arrival strategy

On-arrival: Detecting the emergency vehicle on entering the intersection and then prioritizing the emergency phase. Here the problem is a deceleration of the emergency vehicle as illustrated in Figure 2**(a)** because of the slow movement of the normal traffic volume blocking the emergency vehicle.

Before-arrival: The emergency vehicle is noticed in advance (before reaching the intersection) and signals are planned accordingly so that the emergency vehicle crosses through the intersection without any speed reduction as shown in Figure 2**(b)**.

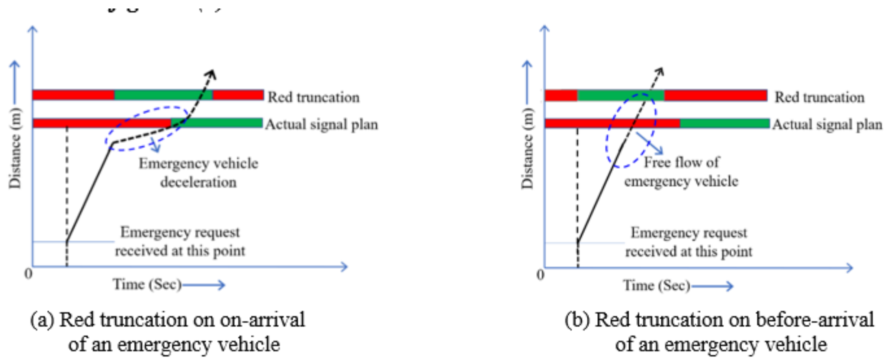

Fig 2. Signal pre-emption scenarios

2.2 Role of green time estimation

If the location of an emergency vehicle in the direction of its flow is known, then the signal lengths are planned accordingly to facilitate a freeway for an emergency vehicle. Green time estimation as per traffic volume is the pivotal part of signal planning. If the estimated green time is more than necessary, then the early green time is allotted for an emergency vehicle leading to green loss as shown in Figure 3**(a)**. Otherwise, if the green time estimated is less than the required, then the green allocation is delayed for an emergency vehicle resulting in emergency vehicle deceleration as depicted in Figure 3 **(b)**. Therefore, accurate green time prediction to clear the traffic volume in front of an emergency vehicle that hinders the speed of an emergency vehicle is a crucial part of the process which is focused on in this article.

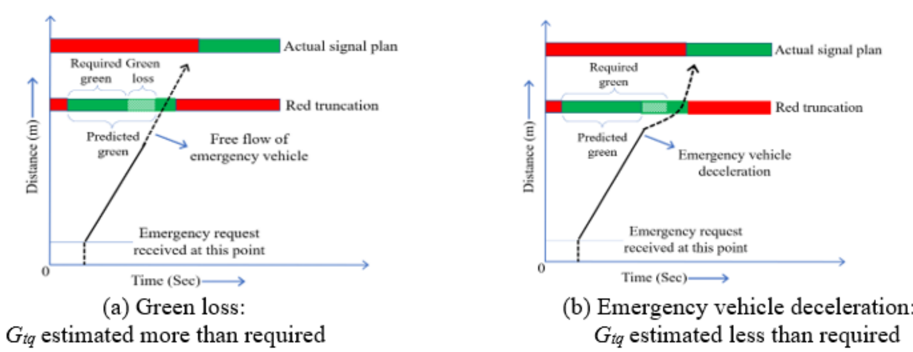

Fig 3. The impact of deviation in green time prediction on the signal operation

2.3 Machine learning models

One of the smart application 'Signal length prediction' highlighted in Figure 1 plays an important role in the design and development of a smart pre-emptive traffic signal control system. As per literature, the machine learning concept is rarely applied in this area. However, the current article focused to demonstrate the efficiency of machine learning in designing emergency vehicle management systems. In this view, the study is presented in two folds; firstly, the identification of a suitable machine learning model for green time prediction and the implementation of an emergency vehicle management system using the selected model. Next, compare the proposed pre-emptive signal controller with the conventional non-pre-emptive signal controller.

Based on the authors' previous research on machine learning[22], five machine learning models namely Linear Regression (LR), Support Vector Regression (SVR), Decision Tree (DT), Gradient Boosting Regression Tree (GBRT), and Convolution Neural Network (CNN) is selected for the current study. LR and SVR are linear models, and DT and GBRT are non-linear models, whereas CNN is a deep network model. CNN functions in two stages; feature extraction and regression with a fully connected artificial neural network. The first stage is also known as the kernel convolution layer where filtering and pooling operations are performed. The filtering operation will generate the feature map, it is carried out to extract the important features from input data that influence the final prediction. Pooling is performed to reduce the data dimensionality thereby reducing the number of computations. The second stage is a fully connected dense layer that is responsible for handling variability in data. The computational complexity of Con1D is ~O(NK)[23] where N is the dimensionality of input data and K is the size of kernel used while training the model.

Kernel convolution is a process in which a matrix of specific size (3x3, 5x5, etc.) numbers known as a filter or a kernel passed over the data instances to transform the input based on filter computed values. The subsequent feature maps are estimated as per eq. (1) and (2) whereas pooling operation is performed as per eq. (3). Max pooling and average pooling are the two ways of pooling and MaxPooling1D () is used in the proposed solution.

$$\mathrm{F}\quad [m,n] = (D^{*}K)\,[m,n] \tag{1}$$

$$(D*K)\,(m,n] = \textstyle\sum_i \sum_j D\,(i,j]*K[m-i,\ \ n-j] \tag{2}$$

∀i = 0 to m-(p-2) // increment i by stride size in each iteration i.e. i = i + x

∀ j = 0 to n-(q-2) // increment j by stride size in each iteration i.e. j = j + x

$$\mathrm{P}[i,j] = \max\left\{\begin{array}{c} D[i,j], D[i,j+1], \ldots D[i,j+(q-1)] \\ D[i+1,j], D[i+1,j+1], \ldots [i+1,j+(q-1)] \\ \ldots \\ D[i+(p-1),j], D[i+(p-1),j+1], \ldots D[i+(p-1),j+(q-1)] \end{array}\right\} \tag{3}$$

Where

m Is the number of rows in matrix D

n Is the number of columns in matrix D

p Is the number of rows in matrix K

q Is the number of columns in matrix K

D Is the input matrix of size [m, n]

K Is the kernel matrix of size [p, q] || p<m, q<n

F Is the matrix of feature map of size [m, n]

x Is the stride size less than m and n

P is pooled/reduced matrix of size [m-x, n-x], and the maximum element in the window of the input matrix covered by the kernel is taken as the element in pooling matrix P.

The fully connected dense neural network functions based on the backpropagation theorem with a linear model as in eq. (4)

$$Y = b + \textstyle\sum_k \sum_i w_{ki} x_{ki} \tag{4}$$

Where b is the bias, Y is the target output, k is the number of hidden layers, i is the number of neurons in each layer and w is the weight of each input feature x. Mean Square Error (MSE) in eq. (5) is used to correct the model accuracy through weight adjustment in each iteration or epoch.

$$e' = \frac{1}{n}\sum_i (Y_i - Y_i'\ )^2 \tag{5}$$

Where e' is the error, Y_i and Y_i' are the target output and predicted value of i^{th} instance and n is the number of instances.

2.4 Operation strategy of the proposed controller

The emergency vehicle is sending its arrival information to the RSU at a signalized intersection along the route through OBU requesting the prioritized green signal. The RSU receives and processes the request to take appropriate action concerning signal activation to facilitate free flow for an emergency vehicle. The process of current green phase pre-emption and prioritization of emergency vehicles is subjected to the time taken by an emergency vehicle to arrive at a signalized intersection. Let T_{ev} be the time taken by an emergency vehicle to reach a signalized intersection from its current location. And let G_{tq} be the green time necessary to clear the normal traffic queued at a signalized intersection in the direction of emergency vehicle flow. An ideal association between 'T_{ev}' and 'G_{tq}' is drawn as eq. (6) to ensure the free flow of an emergency vehicle with a minimum possible green loss at a signalized intersection, where Δt is the signal switching time.

$$T_{ev} == G_{tq} + \triangle t \tag{6}$$

Even though the emergency vehicle is allowed to cross through a signalized intersection without stopping, the speed of an emergency vehicle is reduced due to signal transition and the normal traffic queue in front of it. However, the normal traffic queue at a signalized intersection is the major obstruction for the emergency vehicle flow rather than the red light, as the red light can be truncated with less effort. The signal pre-emption process to manage an emergency vehicle at a signalized intersection is given in procedure 1. As per eq. (6) accurate estimation of T_{ev} and G_{tq} is essential to avoid early green or delayed green allocation for an emergency vehicle. The term t_{diff} is the deciding factor of the signal pre-emption process as described in step 3 of procedure 1 and it is computed based on T_{ev} and G_{tq} as per eq. (7).

$$t_{diff} = T_{ev} - G_{tq} + \triangle t \tag{7}$$

T_{ev} can be approximated using high-resolution data obtained through GPS and sensors. But estimation of accurate G_{tq} based on traffic volume is a complex computational process. More than or less than the required G_{tq} estimation affects the signal operations such as red truncation, phase switching, and green extension as depicted in Figure 3. Therefore, estimation of an accurate G_{tq} is a crucial point in the signal pre-emption process which is focused on in this research work. With this preface, the terms T_{ev} and G_{tq} are estimated as per eq. (8) and (9) respectively.

$$T_{ev} = D_{ev}/S_{ev} \tag{8}$$

$$G_{tq} = f_1(V) \tag{9}$$

Where 'D_{ev}' is the distance between a signalized intersection and the current location of an emergency vehicle at the time of request received by RSU. 'S_{ev}' is the normal speed of an emergency vehicle. 'V' estimated as per eq. (10) is the traffic volume queued at a signalized intersection in the direction of emergency vehicle flow. 'f_1' is a function that receives the traffic volume as input and predicts the green time necessary to clear the corresponding traffic volume. 'f_2' is a function that estimates traffic volume dynamically through video analysis [24].

$$V = f_2(real\ Time\ Video) \tag{10}$$

Eq. (9) is addressed in this article using a convolution neural network. The working principle of the CNN algorithm is presented in the previous subsection whereas the data used to implement the proposed module is detailed in the following subsection.

2.5 Data

The data set plays a vital role in the design and development of machine learning models. As the objective of this research work is to predict the accurate green time necessary to pass through an amount of traffic volume at an instance. Generally, the time required to clear the traffic in one direction is directly proportional to traffic volume, traffic velocity, and road capacity. For simplification, traffic velocity and road capacity are assumed as constants. Hence, traffic volume is an important parameter based on which the green time is estimated. As the focus of the article is to handle the heterogeneity, the traffic volume can be presented in two forms: the count of each type of vehicle (traffic composition) and the Passenger Car Unit (PCU) count. The authors in [22] demonstrated the superiority of traffic composition data over PCU in the process of building a machine learning model. With this reference, traffic composition data is used to develop the green time prediction module.

Procedure 1: Signal pre-emption process		
CP	:	Current phase allotted with green
EVP	:	Emergency Vehicle Phase (direction of emergency vehicle arrival)
RG	:	Remaining green time of the current phase
CG	:	Constant green time
TH_{min}	:	Minimum threshold value
TH_{max}	:	Maximum threshold value
t_{diff}	:	Time difference between emergency vehicle arrival and normal traffic clearance
1	:	Loop Normal Signal Operation if emergency request Go to step 2
2	:	if $CP == EVP$ if $T_{ev} \leq RG$ Extend green time of CP by CG else if $(T_{ev} - RG) \leq TH_{min}$ Extend green time of CP by $(CG + TH_{min})$ else Go to step 1
3	:	else Compute $t_{diff} = T_{ev} - G_{tq} + \triangle t$ if $t_{diff} < TH_{min}$ pre-empt current phase activate green for emergency vehicle else if $TH_{max} \leq t_{diff} \geq TH_{min}$ complete the current phase activate green for emergency vehicle else if $t_{diff} > TH_{max}$ Go to step 1

The traffic in India is highly heterogeneous. However, for simplification purpose, the overall traffic is classified into five categories: two-wheelers, autorickshaws, cars, Light Commercial Vehicles (LCV), and Buses/Trucks. Field observation is conducted in Tumakuru, Tier-II city in Karnataka, India, to know the approximate amount of each type of vehicle crossing the intersection. A four-legged signalized intersection located at the center of the city is observed manually at various times of the day. The data necessary for developing the ML model are synthesized based on field observation.

3 Results and discussion

The current research is carried out in two folds; identifying a suitable machine learning model to predict the green time corresponding to the queued traffic volume and implementing of smart-emergency vehicle management system using identified ML algorithm. Then a traditional non-pre-emptive signal controller and an on-arrival-pre-emptive signal controller are established for the synthesized data. Finally, the results obtained from all three models are compared to show the significance of the proposed model.

Model identification: The selected models including LR, SVR, DT, GBRT, and CNN are implemented in Jupyternotebook, and a suitable model is identified based on the results obtained. 23684 and 16316 instances are used for training and testing the models respectively. The proposed model read the count of traffic composition at a time 't' as input and predicts the green time required to clear the traffic during the emergency phase. The green time (seconds) predicted by each model for test data versus actual green time (seconds) is depicted in Figure 4 by considering 21 random records. The green time predicted by LR, SVR, and DT can easily be distinguished from actual green time. Whereas the green time predicted by GBRT, and CNN almost coincides with the actual green time. This implies that the GBRT and CNN models are suitable for green time prediction in the implementation of SMART-EVMPS. Further, it can be observed that the CNN model performs well than the GBRT, while SVR is not a suitable model for the intended purpose.

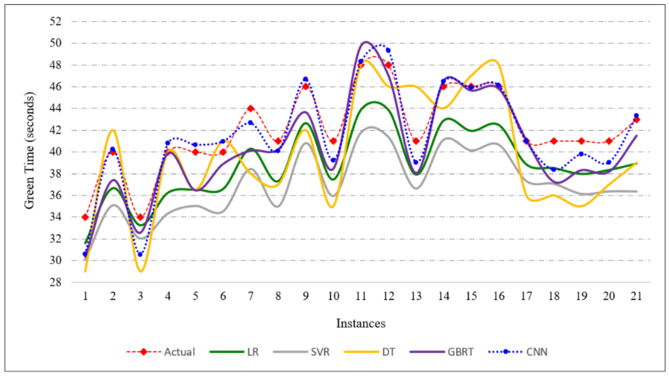

Fig 4. Actual v/s predicted green times

The implemented algorithms are evaluated based on error metrics such as Absolute Error (AE), Median Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Square Error (MSE). The computed error metrics for the models are given in Table 1. The error metrics indicate that the CNN model predicts more accurate and optimized green time compared to other models. R2-score is an additional model evaluation metric used to know the performance of the model and the previous inference is confirmed as per values given in Table 2. The limitation of CNN is that it takes more time for training compared to all other models and it demands more computational power. However, computational capabilities can be facilitated through edge computing.

Table 1. Error metrics

Error Type	LR	SVR	DT	GBRT	CNN
AE	3.20	4.99	4.00	1.90	1.53
MAE	3.09	4.73	3.68	2.08	1.23
MSE	11.57	26.83	18.21	6.36	3.77
RMSE	3.40	5.18	4.27	2.52	1.94

Table 2. Model evaluation metrics

Evaluation metric	LR	SVR	DT	GBRT	CNN
R2-SCORE	0.88	0.74	0.82	0.93	0.96
Train Time	0.00	57.26	0.03	0.86	338.26

Comparative analysis: The existing solutions to manage an emergency vehicle at the signalized intersection are proposed considering the uniforms traffic conditions. Whereas non-uniform traffic condition is the reality in most of the countries. The green time prediction module has a pivotal role in minimization of vehicle delay and wastage of green time, but the estimation of accurate green time necessary to clear the normal traffic accumulated in front of the emergency vehicle is a challenge in case of heterogeneous traffic environment. The proposed study is focussed on this issue. The proposed smart-emergency vehicle management system is able to predict the accurate green time as shown in Figure 4 corresponding to queued heterogeneous traffic volume with five different class of vehicles.

A traditional non-pre-emptive signal controller and an on-arrival-pre-emptive signal controller are considered to illustrate the efficiency of the proposed model performance. The delay encountered by an emergency vehicle is an important parameter to be observed. Hence, the delay is used as an evaluation metric to assess the performance of the proposed model. Numerical analysis is conducted to compute the delay based on the proposed algorithm presented in the methodology section. The delay experienced by an emergency vehicle via three different models including Non-Pre-emptive Controller (NPC), On-Arrival Pre-emptive Controller (OAPC) and CNN-based Before-Arrival Pre-emptive Controller (BAPC) are represented through the box-plot as shown in Figure 5 . The average delay encountered is 86, 25, and 8 seconds for NPC, OAPC and BAPC respectively. In the graph, a negative delay is observed for the proposed model implying wastage of green time. However, a slight wastage of green time is acceptable in case of emergency situations. Therefore, though the green time is wasted with the proposed model, it is the best model among the three.

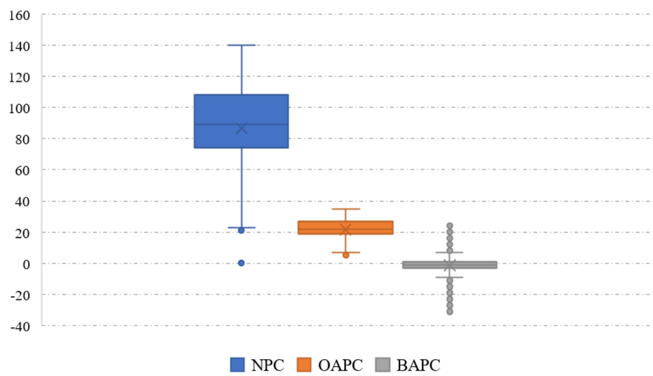

Fig 5. Delay encountered by an emergency vehicle

In most cases, the emergency vehicle experienced zero delays with a proposed system. However few times it experienced a slight delay due to the dynamic nature of normal traffic arrival in between the green time allocation and emergency vehicle reaching the intersection and inaccurate predictions as well, which is not addressed in the current study, thus resulting in an average delay of 8 seconds. The numerical results clearly showed that the proposed system outperformed the conventional system. However, the proposed system has a further scope of enhancement. If the arrival rate and intersection saturation of the normal traffic is well known, then the performance of the system can further be improved in terms of delay and green wastage mitigation.

4 Conclusion

The traffic congestion on roads deteriorates the travel speed and lowers safety as well, particularly at signalized intersections. Emergency vehicles stuck in congestion at an intersection can cause life loss or property loss. Hence, an emergency vehicle deserves a prioritized signal to get through the signalized intersection without any deceleration. In this view, an attempt has been made in the current article to develop a machine-learning-based pre-emptive traffic signal controller to ensure the free flow of an emergency vehicle across the signalized intersection. Various functional units are involved in implementing a pre-emptive signal control system and the green time prediction unit is one of them. The current study is focused on green time prediction based on traffic composition and volume. The study is conducted in two folds; identify a suitable machine learning (ML) model to predict the green time and use the selected model to design the proposed system. Four different ML algorithms including LR, SVR, DT, and GBRT are identified based on literature to explore the best model for implementing the proposed solution. The simulation results revealed that the green time predicted by CNN showed less deviation from the actual green time. The models are evaluated through an R2-score which confirms the best performance of CNN with a 0.96 score. The green time prediction module shares a pivotal role in the system as more/less green time prediction can waste the green time or block the free flow of emergency vehicles. The mean delay for an emergency vehicle is 86 and 25 seconds as per conventional non-pre-emptive controller and on-arrival-pre-emptive signal controllers respectively, whereas it is 8 seconds in the case of the proposed system. Green time prediction under heterogeneous traffic conditions is a challenge that can be addressed through a proposed model. Analytical models are widely used to estimate the green time as per existing research works concerned with emergency vehicle management. However, ML models are also in use, but deep learning models are applied rarely, and CNN is applied in current work.

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