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Long-short term traffic prediction under road incidents using deep learning networks

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***Abstract*—This paper investigates the effectiveness of multivariate deep learning models for traffic flow prediction with road incidents. Multiple features of the data are considered in the analysis including traffic features, road incident features and cyclical features. Three multivariate deep learning models based on the stacked LSTM network, the CNN LSTM network, and the Autoencoders-LSTM network are developed for long-short term traffic forecasting under road incidents. The results obtained from the analysis are then compared to determine the best suitable approach.**

***Index Terms*—Traffic prediction, Multivariate learning model, Stacked LSTM network, Autoencoders LSTMs, 1-D convolution neural network.**

I. Introduction

Knowing traffic conditions in advance is essential for traffic engineers, planners, and individuals. The design of traffic monitoring system and the prediction of traffic flow have become more and more important in metropolitan planning worldwide, especially with the introduction of Intelligent Transport Systems (ITS) infrastructure such as variable message signs, speed cameras etc. For a safe road control, improvement of traffic monitoring system is essential. Traffic monitoring system based on wireless sensor networks [1] and embedded web technology [2] have been designed to detect city transport vehicles. Traffic flow prediction is also important for advanced traveller information systems, traffic management centres, intelligent public transport and commercial vehicle operations. For efficient traffic controls, long and short term prediction of traffic flow under road-incident conditions has been a research challenge over the years. There are three conventional techniques for predicting the tendency and movements of time series data: classical regression methods, traditional statistical models, including exponential smoothing, moving average and the Auto-regressive Integrated Moving Average model (ARIMA), and machine learning models.

Nowadays, artificial neural network (ANN) and recurrent neural networks (RNN) are widely used for road traffic prediction. An ANN model is a type of machine learning model in which every algorithm learns patterns from data and then predicts for the future. It contains interconnected neuron networks, which can study patterns from the information fed to the machine and identify trends in the data and adapt to the environment. A recurrent neural network (RNN) is also a type of machine learning model. It works well with time-series data. The structure of the RNN consisting of the nodes interconnected with each other allows the network to remember previous information fed into the network. RNN suffers from a vanishing gradient problem [3]. Looping constraints enable the model to keep the error, allowing the machine to study the data and link further to historical data with a more oversized time frame. However, despite getting a relatively good result, the RNN also has a typical neural network limitation about short-term memory. It has difficulty carrying information from earlier time steps to later ones for a long sequence.

As the properties of time series data include dependency, previous inputs are required to achieve accurate results. In both ANN and RNN, all inputs and outputs are independent, which provide inaccurate results when predicting time series data. Therefore, there is a need to explore efficient methods which bring in a multitude of data through deep modelling architecture. As technology improves and machines become more advanced, deep learning approaches become very popular.

Examples of classical deep learning approaches include the multilayer perceptron model (MLP), the convolutional neural network (CNN), the long short-term Memory network (LSTM) and the gated recurrent unit (GRU). The MLP is a class of feedforward ANN with three connected layers, including one hidden layer. The model with more than one hidden layer is called a deep ANN. Also, CNN is a class of ANN models with multiple layers. The convolutional layer of the CNN can extract the valuable features of the data fed into the model, such as images and text, making it very useful in natural language processing and image processing.

In the case of time series data, an 1-D convolutional filter is used in order to extract high-level features. The parameter sharing in the CNN allows equal weights to be applied across the layer, thus reducing the number of parameters in the model and improving the model's efficiency. Using the CNN features offered in predicting time series data, the results are more accurate. The LSTM proposed by Hochreiter and Schmidhuber

[4] is a special kind of recurrent neural networks. It was designed to elaborate sequences of data preserving either short or long term dependencies. It can predict future values maintaining the noteworthy influence of the past trend and adequately reproducing it into forecasting. In 2014, Cho et al. [5] introduced the GRU, a variation of RNN, having fewer parameters, less complexity and no output gate. For some specific smaller datasets, it has shown better performance than the LSTM.

As traffic data are considered imbalanced, classical machine learning algorithms cannot correctly represent the data distribution characteristics. For handling imbalanced datasets, various data sampling techniques have been used, such as removing abundant data from the majority class (undersampling) or adding new data to the minority class (oversampling), and ensemble approaches have been applied to adjust the class distribution of the training data set [5]–[15].

Bagging/boosting-based ensemble methods were used to classify imbalanced data [9]. Nejatian et al. [12] proposed a sub-sampling and ensemble clustering method for learning tasks in which the number of samples in a minority class is less than the number of samples in other classes.

Although various deep learning techniques are available, further work is needed in order to achieve effective prediction for imbalanced freeway traffic data. For prediction of multiple output with multiple inputs using the dataset with various classes, existing prediction models have limitations due to gradient vanishing/exploding, short term memory, long training time and over-fitting.

This paper presents three deep learning models to predict freeway traffic under road incidents using an 8-class dataset. These models include a stacked LSTM, a CNN LSTM and an autoencoders LSTM neural networks. The rest of the work is structured as follows. The methodology and the dataset are presented in Sections II and III. Experimental results are discussed in Section IV and a conclusion is given in Section V.

II. Methodology

This section concerns the deep learning design for long-term and short-term predictions involving multiple inputs and multiple outputs. The prediction procedure includes the following key concepts.

A. Pre-processing

The pre-processing procedure involves the following steps.

- The incident and downstream-incident messages were converted to Boolean type data, having value 1 if an incident occurs and 0 otherwise.
- Due to missing data of traffic variables, interpolation technique was applied. Missing incident features were treated as no incident.
- Splitting the dataset (df) into two subsets, namely, the training set (80%) and the test set (20%).
- As the data attributes have different scales, feature scaling was performed to avoid training with inconsistent units and to take into account the degree of difference in each attribute. In addition, the Min-Max scaling technique was employed to normalize data to 0 and 1 range.
- The last step of pre-processing involves reshaping the dataset into a three-dimensional array, i.e.,

  df.shape = (number of samples, window size, features).

  In this study, the window size is 10, and the number of features is 8 features.

B. Model Architecture

The designed model was performed with the help of hyperparameter tuning. A grid search algorithm with a set of initial hyperparameters was used to determine the best combination of hyperparameters including the activation function, optimizer, learning rate, dropout rate, batch size, and the number of neurons. In our simulation, the grid search algorithm gave the results of the activation function = "relu", optimizer ="Adam", learning rate =0.001, dropout rate=0.2, batch size=10, and number of neurons presented in Fig. 1 for the stacked LSTM, the CNN LSTM and the Autoencoders LSTM architectures. In addition, the early stopping technique is employed to avoid the overfitting problem.

C. Training-Prediction process

The training set was used to train the model and the test set was used for validation. The process is as detailed below.

- Training process
  - The models were built based on the hyperparameters obtained from the grid searching algorithm,
  - The early stop technique was employed to interrupt the training when no progress on the training set is measured,
  - The best model was thus obtained from the previous epoch,
  - The training time was recorded and Root mean square errors (RMSE) was calculated.
- Prediction process
  - Traffic prediction was obtained via the model fitting.
  - Root mean square errors (RMSE) were calculated.

III. Data Description

For predictive analytic, an edge-scaled dataset of traffic flow is obtained from an arterial road of the Kwinana Smart Freeway starting from Farrington Road (NPI link 2) to Narrows Bridge (NPI link 14) in Perth WA, Australia. The traffic dataset collected by the Vehicle Detector Sites (VDS) placed on various road edges of the Kwinana Freeway Northbound are from the Main Roads, Western Australia (MRWA).

Fig. 3 shows the traffic jam caused by road incidents between 8:30-10:30 and 12:00-12:30.

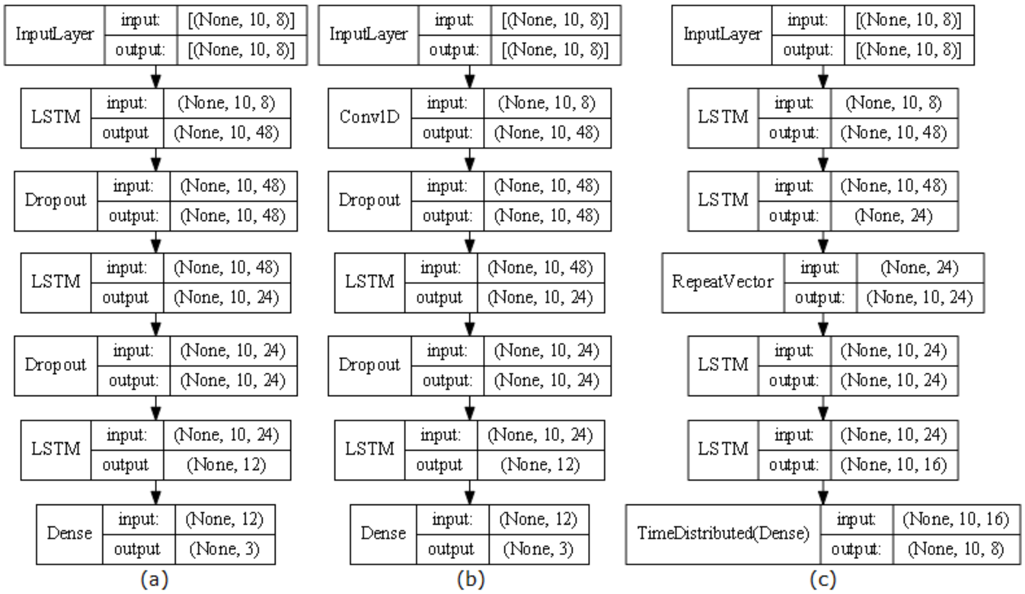
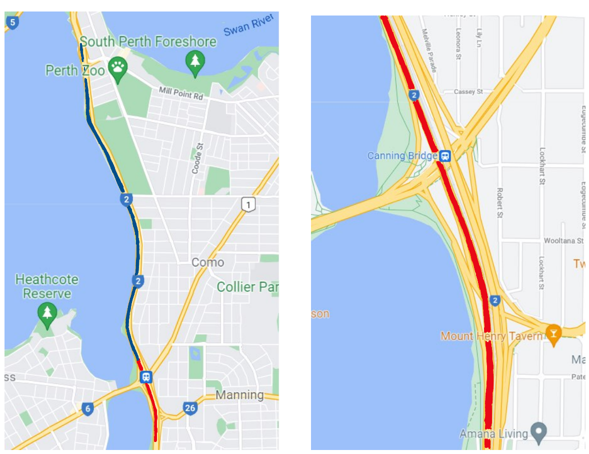
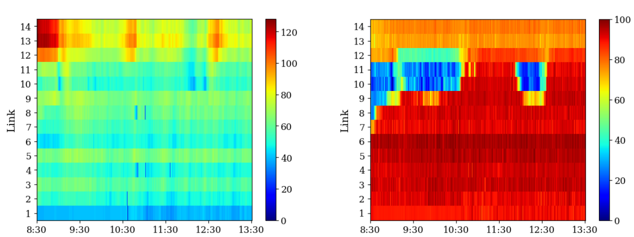


Fig. 1. Model architectures of machine learning models: (a) LSTM; (b) 1-D CNN LSTM; (c) Autoencoders LSTM.



(a) (b)

Fig. 2. The study region: (a) the study road (–) with its downstream (–); (b) a diamond interchange design of the study road.



(a) flow rate (veh/min) (b) speed (km/h)

Fig. 3. Heatmap of traffic variables on the study period.

The traffic data obtained during the study period, between 1 January and 25 October 2018, comprises a number of 1-min observations. The road incident data was obtained from the study road and its downstream road. Details of the dataset

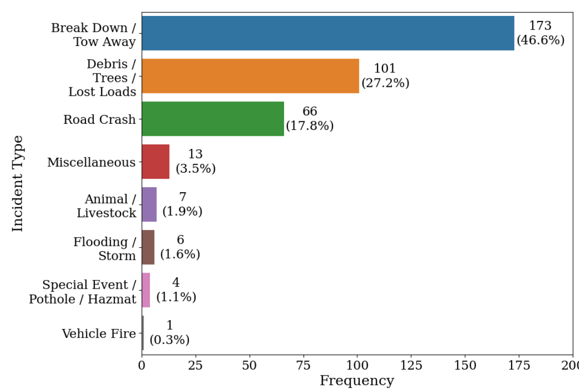


Fig. 4. Statistics of road incidents on the Kwinana Freeway northbound during the study period (1/01/2018-25/10/2018).

preparation are given in the following subsections.

A. *Traffic flow dataset*

The dataset comprises historical 1-min observations of traffic flow characteristics including the flow rate (veh/min), the speed (km/h) and the occupancy. The sample size of observations is 429,120. The study area (the red curve) with its consecutive downstream road (the black curve) is shown in Fig 2(a). This area was chosen for the study as its consecutive downstream road had the largest number of road incidents during the study period.

In addition, it is a diamond interchange road with a northbound entrance ramp and southbound entrance and exit ramps and an additional bus-only ramp connecting to the median lanes of the study area as shown in Fig. 2(b).

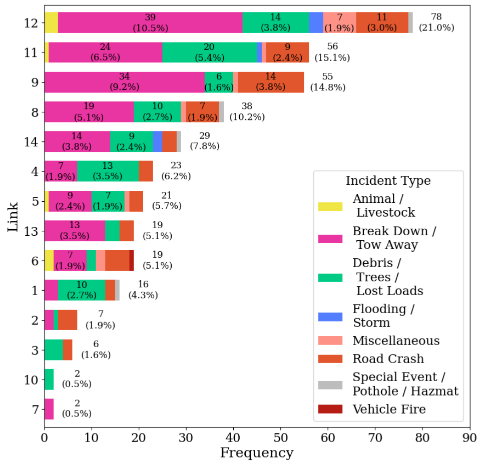


Fig. 5. Link road incidents on the Kwinana Freeway northbound during the study period (1/01/2018-25/10/2018).

TABLE I
TYPES OF ROAD INCIDENTS

Waze alert subtype	Hazard on shoulder car stopped
	Jam heavy traffic
	Jam stand still traffic
	Jam moderate traffic
	Hazard on road construction
	Others
WebEOC Incident Type	Break Down / Tow Away
	Road Crash
	Debris / Trees / Lost Loads
	Vehicle Fire
	Animal / Livestock
	Others
WebEOC Traffic Impact	Left Emergency Lane Blocked.
	Lane Closures
	Left Emergency Lane Blocked.
	Left Lane(s) Blocked
	Exercise Extreme Caution
	Others

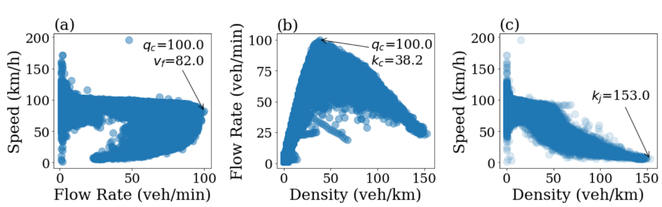


Fig. 6. Fundamental diagrams showing relationship of two traffic variables: (a) speed (km/h) and flow rate (veh/min); (b) flow rate (veh/min) and density (veh/km); (c) speed (km/h) and density (veh/km).

B. WebEOC dataset: Road Incident data

The study considers various types of road incidents such as Waze alert subtype, WebEOC incident type and WebEOC traffic impact presented in Table I. The incident dataset was obtained from the WebEOC software that MRWA uses to track actions and decisions relating to incidents.

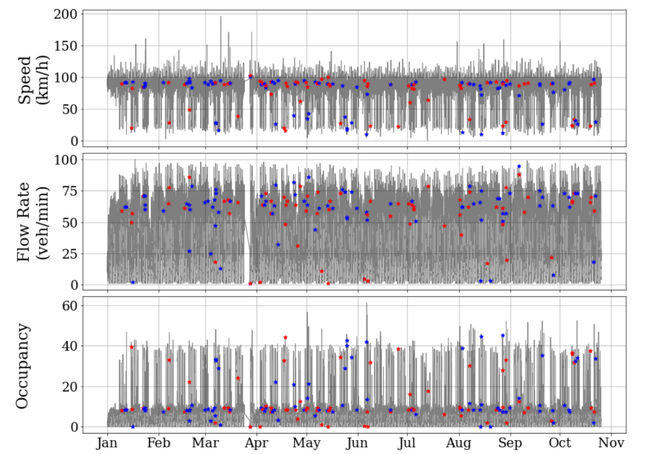


Fig. 7. Variations of traffic flow rate, speed and occupancy on the study road with road incidents (*) and downstream incidents (*)

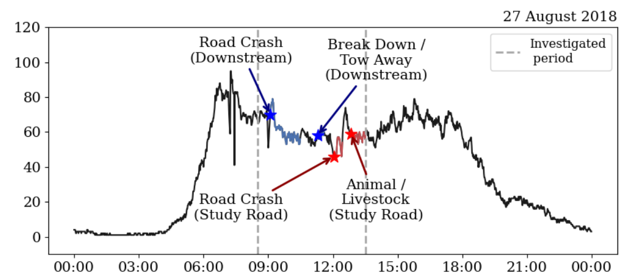


Fig. 8. Variation of traffic flow with time. The figure also shows the study time period between 8:30 and 13:30 (vertical dashed lines) for investigation of forecast accuracy, duration of the downstream incidents (blue curve), and the study road incidents (red curve).

The dataset was recorded every 15 minutes for the same study period. The statistics of road incidents are shown in Fig. 4 and Fig. 5. The top high road incidents occurred on the study road and its consecutive downstream.

It is noted that three incident types often occur, including breakdown / tow-away, debris/Trees/lost loads, and road crashes. Road incidents caused by these three types are more common than others. Fig. 6 shows the fundamental traffic flow diagrams on the study road, i.e., the relationship of the speed and the flow rate, the relationship of the flow rate and the speed, and the speed and the density, respectively.

Fig. 7 shows cyclical features of the freeway traffic on the study road with incidents (red star) and its downstream incidents (blue star) on 27 August 2018. It is noted that some road incidents are the common cause of traffic jams.

C. Study data

The study data used for this analysis is generated by merging two datasets of traffic variables and road incidents using a timestamp matching.

The merged data was extracted to preserve their significance for traffic prediction. The dataset with eight features was obtained for predictive analytics. These features are traffic flow rate, speed, occupancy, road incident, downstream incident, sine hour, cosine hour and holiday.

IV. Experimental Results

As road crash usually occurs when traffic becomes unstable and reduces freeway/highway capacity, for investigating the long-term forecast accuracy of the three established deep learning models, the study time period between 8:30 and 13:30 with the existence of road incidents as shown in Fig. 8 is chosen in this study.

Long-term traffic predictions of traffic flow rate (veh/min), speed (km/h) and occupancy from 8:30 to 13:30 (300 minutes) obtained from the stacked LSTM, the CNN LSTM and the Autoencoders LSTM neural networks are shown in Fig. 9 to Fig. 11, respectively. Fig. 9 shows long-term predictions obtained from the stack LSTM network. The results show a clear long-term trend of traffic speed and occupancy, but give poor prediction of traffic flow. Predicted values of traffic flow rate do not match its actual distribution, especially around the incident time 12:00, while prediction results of the speed and the occupancy, compared with their actual values show somewhat in the same trend between 8:30 and 13:30.

For the CNN-LSTM network, the results in Fig. 10 look similar to the ones obtained from the stacked LSTM network, but less variation of predicted values from the actual values of traffic variables. Using the Autoencoders-LSTM network, long-term predictions of traffic flow rate, speed and occupancy are shown in Fig, 11. Prediction results of the speed and the occupancy are reasonable, but not accurate for the flow rate.

For short-term prediction using three learning models, traffic flow rate, speed and occupancy are predicted from the time that road incidents occurred to the next 30 minutes. As the downstream and the study road incidents occurred respectively at 9:00 and 12:00, short-term traffic flow predictions with the downstream incident (blue star) between 9:00 and 9:30 and the study road incident (red star) between 12:00 and 12:30 were evaluated.

For short-term prediction using three learning models, traffic flow rate, speed and occupancy are predicted from the time that road incidents occurred to the next 30 minutes. As the downstream and the study road incidents occurred respectively at 9:00 and 12:00, short-term traffic flow predictions with the downstream incident (blue star) between 9:00 and 9:30 and the study road incident (red star) between 12:00 and 12:30 were evaluated. Fig. 12 shows short-term traffic flow predictions obtained from the stacked LSTM (columns 1), the CNN LSTM (columns 2) and the Autoencoders LSTM (columns 3) after the existence of the downstream incident and the study road incident, respectively.

The results show that traffic flow predictions of the speed and the occupancy obtained from three models are somewhat the same trend as the actual data, but not accurate for the flow rate.

It is noted that high incident rate, existing in the low traffic volumes, reduces roadway traffic capacity as shown in Fig. 12.

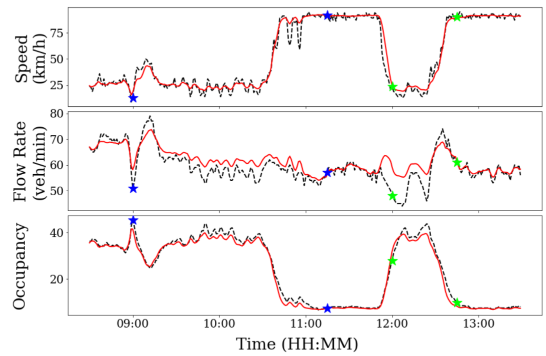


Fig. 9. Long-term predictions obtained from the stack LSTM network: actual values (a dashed black line) and predicted values (a solid red line) with the study road incidents (∗) and its downstream incidents (∗).

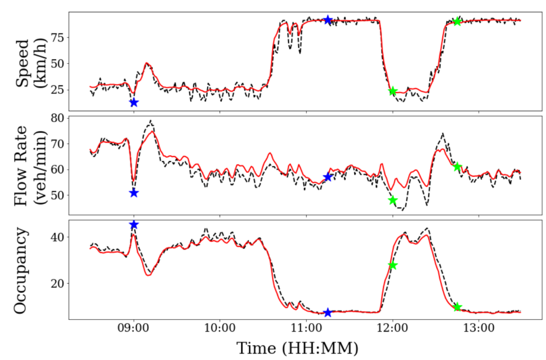


Fig. 10. Long-term predictions obtained from the CNN LSTM network: actual values (a dashed black line) and predicted values (a solid red line) with the study road incidents (∗) and its downstream incidents (∗).

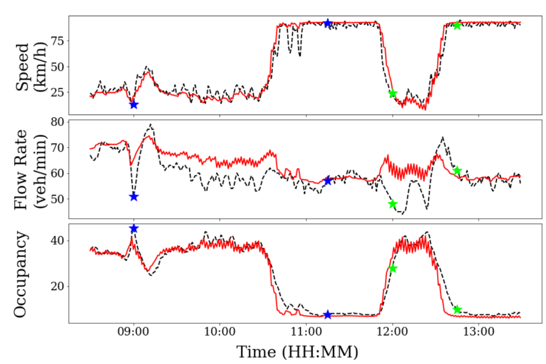
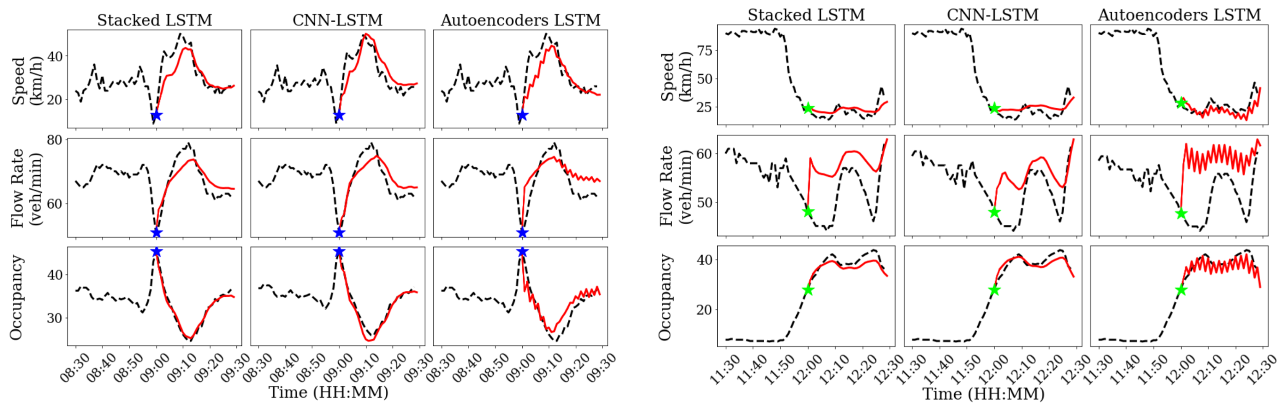


Fig. 11. Long-term predictions obtained from the Autoencoders LSTM network: actual values (a dashed black line) and predicted values (a solid red line) with the study road incidents (∗) and its downstream incidents (∗).

In this study, the root mean square error (RMSE) of approximation is used to measure goodness of fit for the three models. Table II shows the averaged RMSE obtained in each case. It is noted that the RMSE for the test set in each case is a bit higher than that of the training set. It is reasonable because the test set contains the data that the model hasn't seen before. The RMSEs in estimating the flow rate and speed obtained from the CNN LSTM model are much smaller than those obtained from the other two models.



(a) 9:00 am to 9:30 am (b) 12:00 to 12:30 pm

Fig. 12. Short-term predictions obtained from the stack LSTM (column 1), the CNN LSTM (column 2) and the Autoencoders LSTM (column 3) networks: actual values (a dashed black line) and predicted value (a solid red line) with the downstream incidents (∗) and the study road incidents (∗).

TABLE II
ROOT MEAN SQUARE ERROR (RMSE)

Models	Dataset	Speed	Volume	Occupancy
Baseline	**Train**	12.9261	10.0373	5.4275
	Test	12.4896	9.4569	5.0512
Stacked LSTM	**Train**	4.2438	5.0971	0.9279
	Test	4.8243	5.2053	0.9325
CNN LSTM	**Train**	4.2414	2.6498	0.7298
	Test	4.9198	2.7271	0.7550
Autoencoders LSTM	**Train**	5.0703	6.1089	1.6157
	Test	5.7315	6.0571	1.5478

V. CONCLUSION

Multivariate machine learning models have been designed based on the stacked LSTM, the CNN LSTM and the Autoencoders LSTM architectures to forecast freeway traffic under road incidents. Future values of traffic flow rate, speed and occupancy in a long-term period and a short-term period are predicted. The results indicate that the designed model using the CNN LSTM architecture is more suitable for traffic flow prediction under road incidents.

VI. ACKNOWLEDGMENTS

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