IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received October 28, 2018, accepted November 14, 2018, date of publication December 5, 2018, date of current version December 31, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2884933

Hybrid Traffic Forecasting Model With Fusion of Multiple Spatial Toll Collection Data and Remote Microwave Sensor Data

YINLI JIN[1,2], ERLONG TAN[1,2], LI LI[1,2], GUIPING WANG[1,2], JUN WANG[3], AND PING WANG[1,2], (Member, IEEE)
[1]Institute for Transportation Systems Engineering Research, Chang'an University, Xi'an 710064, China
[2]School of Electronics and Control Engineering, Chang'an University, Xi'an 710064, China
[3]Toll Collection Center for Shaanxi Freeway, Xi'an 710021, China

Corresponding author : Ping Wang (wang0372@e.ntu.edu.sg)

This work was supported in part by the National Natural Science Foundation of China under Grant 51505037, in part by the Xi'an Intelligent Freeway Information Fusion and Control Key Laboratory under Grant 201805062ZD13CG46, in part by the China Postdoctoral Science Foundation under Grant 2016M600814, in part by the Key Research and Development Program of Shaanxi Province under Grant 2018ZDCXL-GY-05-04 and Grant 2018ZDCXL-GY-05-07-02, and in part by the Fundamental Research Funds for the Central Universities under Grant 300102328401 and Grant 300102328205.

ABSTRACT In order to forecast the traffic flow more precisely, a novel hybrid model is proposed with multiple sources of traffic data in the spatiotemporal dimension. In the practical application of the proposed model, multiple sources of data are captured and fused from five toll collection gates and one remote microwave sensor based on the correlation analysis. A hybrid model, including the structure of stacked autoencoders and long short-term memory, is used. Stacked autoencoders are used to extract the spatial features. Long short-term memory is used to learn the temporal features. The comparisons of the hybrid model, non-hybrid model, fused data, and non-fused data are provided. The effectiveness of the hybrid model and the fused data demonstrated the best performance. The fused data presented more effective forecast, which encourages that the forecasting model could include more data source to improve the accuracy. Meanwhile, the selection of a suitable model should also be studied for better forecasting result in consideration of difference feature of the data source. The high-accuracy prediction could contribute to further traffic control and prompt the development of the intelligent transport system.

INDEX TERMS Fusion, hybrid model, microwave sensor data, traffic forecasting, toll collection data.

I. INTRODUCTION

The accurate and reliable traffic forecasting is highly desired for travelers, transportation agencies and public [1]–[3]. However, it is hard to precisely predict the traffic flow considering the complexity of real situation with various disturbance [4]. The successful prediction of traffic information firstly relies on the quality of traffic data obtained onsite [5]. Inductive loop detector (ILD) is the most common device installed on freeway to capture the information of volume [6]. But more and more reports indicate that data captured from current ILD are deviated from the ground-truth [7], [8]. Without interference of traffic, non-intrusive traffic detectors are further developed such as remote traffic microwave sensor (RTMS) and traffic video detector equipment (TVDE). Fig. 1 shows the situation and the features of three types of detection equipment. Studies have confirmed the accuracy of these data is higher and with more detailed records than that of ILD [2], [9], [10].

Toll collection data is a reliable data source compared to the measured traffic data [4]. Especially in China, charging system has been fully-established in the closed large-regional road network to operate freeway. Huge amounts of toll collection data, in which every vehicle information with entrance/exit time/place have been accumulated. The precise origin and destination information for each vehicle driving on the freeway are closed related to the traffic flow tendency within every road segment [11].

Neural networks and regression models are widely used in prediction of traffic flow and travel time recently [12]–[14]. The combination of the fast-developed deep learning-based algorithm and massive data accumulation acquired via the ILD/RTMS/charging etc. in the daily operation of freeway can obtain more accurate prediction results. However, it is not an easy task to fuse multiple sourcing data. Each kind of data source has its own characteristics. It is worth exploring the fusion technology for predicting more accurately in

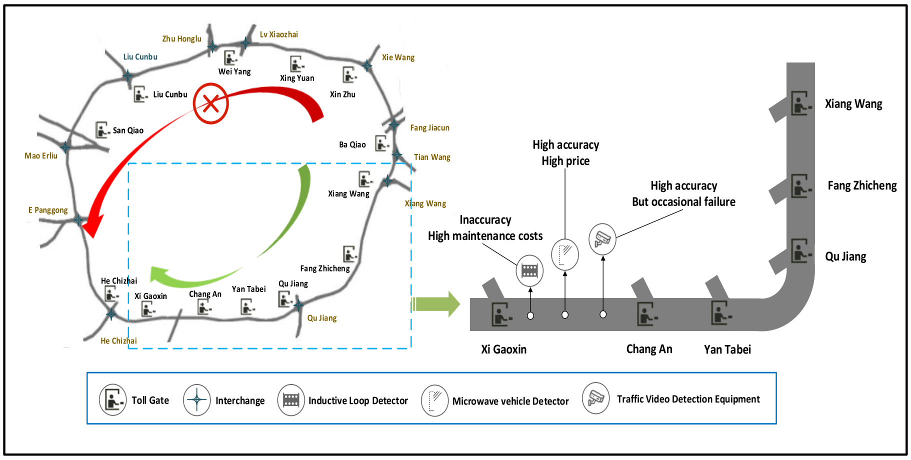

FIGURE 1. **The geometric map of the Xi'an RaoCheng freeway and the detection equipment in target section. The traffic condition can be captured by (a) inductive loop detector(ILD): inaccuracy and high maintenance costs, (b) microwave vehicle detector(MVD): high accuracy and high price, (c) traffic video detection equipment(TVDE): high accuracy but occasional failure.**

consideration of various data characteristics. In this paper, we proposed a novel hybrid model to predict traffic flow based on deep learning-based algorithm to fuse spatiotemporal traffic information. A hybrid model combined stacked autoencoders (SAEs) and long-short term memory (LSTM) are proposed with data fusion. The data collected from the toll collection was fed into SAEs model to extract the spatial characteristics, and the data collected from RTMS and TVDE are fed into LSTM model to learn the temporal features. The combined spatiotemporal features are utilized to predict traffic volume.

This paper is organized as follows: Section II introduces related work of recent deep learning-based algorithm using in traffic flow prediction. A hybrid traffic forecasting model are proposed and provided in Section III. Section IV provides details of experimental results and the performance evaluation of the proposed model. Section V presents a discussion and concludes the paper.

II. RELATED WORK

With the rapid development of technology recently, the application of deep learning approaches to the prediction of traffic flow has received a great deal of attention from both investors and researchers [2], [4], [5], [15]. Multi-dimensional data sources and various models have been proposed to forecast traffic flow and have achieved higher accuracy. We summarized previous research on traffic flow prediction combining or not combining multiple data and models.

The short-term traffic flow prediction has been conducted since the 1980s [15]. There are numerous different prediction methods that have been used for traffic volume prediction, such as the Kalman filtering [15], [16], the support vector machines (SVM) [17], the autoregressive integrated moving average (ARIMA) [18]–[20], and the k-nearest neighbor [21]. The accuracy of prediction is always affected by many factors such as upstream flow situation, weather condition and so forth. The underlying correlation to predict traffic flow might possibly be improved with the rise of the deep learning. Huang *et al.* [4] first applied a deep belief network (DBN) to capture the spatial-temporal characteristics in intelligent transportation system (ITS). Recurrent neural networks (RNNs), including a feedback from previous state to current state, are powerful model for dynamics scenarios [22], [23]. Fang *et al.* [24] converted spatiotemporal information into one-dimensional data using RNN. As for LSTM, a variant of RNN, integrated memory units to disentangle vanishing and exploding gradients in conventional RNNs, so it can capture longer features for time series forecasting [2], [25]. The LSTM model with weather conditions highlighted the significant improvements attainable of multisource data [8], [26], [27]. Ali and Mahmood [28] synthesized that LSTM is best suited for temporal traffic data and SAEs can handle non-liner spatial data effectively. Table 1 shows the review of different models for prediction.

The SAEs always achieve excellent performance on extracting deep features [30]. Duan *et al.* [31], [32] at first used temporal data to predict and then applied SAEs model with spatial-temporal data to achieve better accuracy. In addition, they also evaluated the performance of dissimilar SAEs, which indicated that combining multiple models with different parameters is of significance for precisely predicting [32].

Now, with the increase of various data sources and deeply understanding of the characteristics of deep learning models, hybrid models are of great potential in the prediction of traffic flow. Wu *et al.* [33] established a hybrid model highlighted the advantages of various deep learning architectures for traffic forecast. The SAEs model and LSTM model have been combined to forecast stock price, in which SAEs is applied to reduce dimensions and LSTM is utilized to forecast future stock prices [30]. In addition, the convolutional neural network(CNN) extracting the spatial features and LSTM

TABLE 1. Literature of models for predicting various traffic status.

First author	Years	Models	Data dimentions	Prediction horizon	Predicts
Wenhao Huang [4]	2014	DBN	Spatiotemporal	15,30,45,60	Flow
Zheng Zhao [25]	2017	LSTM	Spatiotemporal	15,30,45,60	Flow
Yuhan Jia [26]	2017	LSTM, DBN	Temporal	10,30	Flow
Yisheng Lv [29]	2014	SAE	Temporal	15,30,45,60	Flow
Leelavathi [34]	2016	SAE	Spatiotemporal	15,30,45,60	Flow
Yangdong Liu [35]	2017	LSTM	Temporal	5,10,20,30,60	Travel Time
Haiyang Yu [36]	2017	CNN+LSTM	Spatiotemporal	2,4,6,20,40,60	Flow
Zongtao Duan [37]	2018	CNN+LSTM	Spatiotemporal	30	Flow

capturing the temporal information are combined for predicting [33], [37]. In this paper, hybrid model is also studied for better prediction of the traffic flow with multiple sources of data.

III. METHODOLOGY

The traffic condition of target section is inevitably influenced by spatial or temporal information extracted from related historical data. In what follows, we are interested in mining the spatial characteristics from upstream Toll Gate(TG) entrances data, for which we choose the SAEs structure, and extracting the temporal characteristics within the calibrated data(CTR) by TVDE data and RTMS data, for which we choose the LSTM structure.

A. DATA DESCRIPTION

The raw dataset used in this paper was collected from TGs, TVDE and RTMS on Xi'an RaoCheng freeway in Shaanxi Province. Charging data of TGs are selected the inner direction with three traveling lanes in this paper. One of busiest arterial roads segment is selected with more than 50,000 vehicles passing this road segment per day. The nearest upstream TG, named Chang An Station, is one of the busiest TG in Shaanxi Province. The selected cross-section (K53+950) is located between Chang An Station and Xi Gaoxin Station. Fig. 2 shows the correlation between target traffic flow data and upstream TGs entry data. It can be seen that there is great impact when it is within a certain range from the target section. From the correlation analysis, other four upstream TGs, named Yan Tabei, Qu Jiang, Fang Zhicheng and Xiang Wang, are considered to be contributor to estimate traffic flow at the cross section. Besides, traveler who is going to pass the target section would choose another direction if he or she wanted the shortest path or least cost.

In order to process the original data into candidate data that could be feed into model straightly, we have to preprocess the data first. The first step is to filter out the outliers by the interval between exit time and entrance time. The second step is to compute the traffic volume from the original statistical record by the entrance time. The section volume data has been calibrated by RTMS and TVDE. The Shaanxi Province Traffic Management Bureau in China ensures that the calibrated data is highly accurate as they are used for monitoring. the traffic flow is aggregated into 15, 30, 45, 60 minutes from the detector, respectively. At the same time, the same preprocessing is carried out for each toll gate. Both the target section point and involved upstream TGs are marked on the indicating map of Xi'an RaoCheng freeway in Fig. 2. Data are extracted from April to May, 2018 as the sampling dataset of this experiment. The data were divided into two subsets: the first six weeks data employed for training, and the remaining data about two weeks employed for testing.

B. STACKED AUTOENCODERS

An autoencoder(AE) is a neural network (NN) that attempts to extract the most prominent features of input data. That is to say an AE could reconstruct its input with less characteristics. Three AEs depicted in the top of Fig. 3. Every AE has a three-layer structure to reconstruct input layer, which contains encoder part and decoder part [34]. The encoder part is a mapping from input vector **x** to hidden representation **h**, and the decoder part maps hidden vector **h** into reconstruction **r**. The input vector **x** has same number units with reconstruction vector **r**. After non-linear operation of an AE, the features among the input data can be obtained in the hidden layers. The nonlinear transformation is given by:

$$h(\boldsymbol{x}) = f(\boldsymbol{w_1}\boldsymbol{x} + \boldsymbol{b_1}) \tag{1}$$

$$r(\boldsymbol{x}) = f(\boldsymbol{w_2}h(\boldsymbol{x}) + \boldsymbol{b_2}) \tag{2}$$

where $\boldsymbol{x}$ represents the input vector, $\boldsymbol{w_1}$ and $\boldsymbol{w_2}$ are the encoding weight matrix and decoding weight matrix, respectively. $\boldsymbol{b_1}$ and $\boldsymbol{b_2}$ are the encoding bias vector and decoding bias vector. $h(\boldsymbol{x})$ is the output of encoding layer. $r(\boldsymbol{x})$ is the output of decoding layer.

A stacked autoencoders (SAEs) model is constructed by multilayer autoencoders to capture significant features from massive data, which can be used to convert high-dimensional data to low-dimensional codes. The first layer is input layer for attaining training set. After the first layer is determined, the hidden layer of the kth AE is considered as the input of the kth hidden layer. According to this method, a SAEs model could be constructed hierarchically. The structure of SAEs model can be seen in Fig.3. Meanwhile, two procedures are included in training a SAEs model: pretraining and fine-tuning [31]. Pretraining trains every AE by the greedy layer-wise unsupervised learning algorithm to optimize the weights of each layer while fine-tuning adjusts all the parameters in the SAEs model.

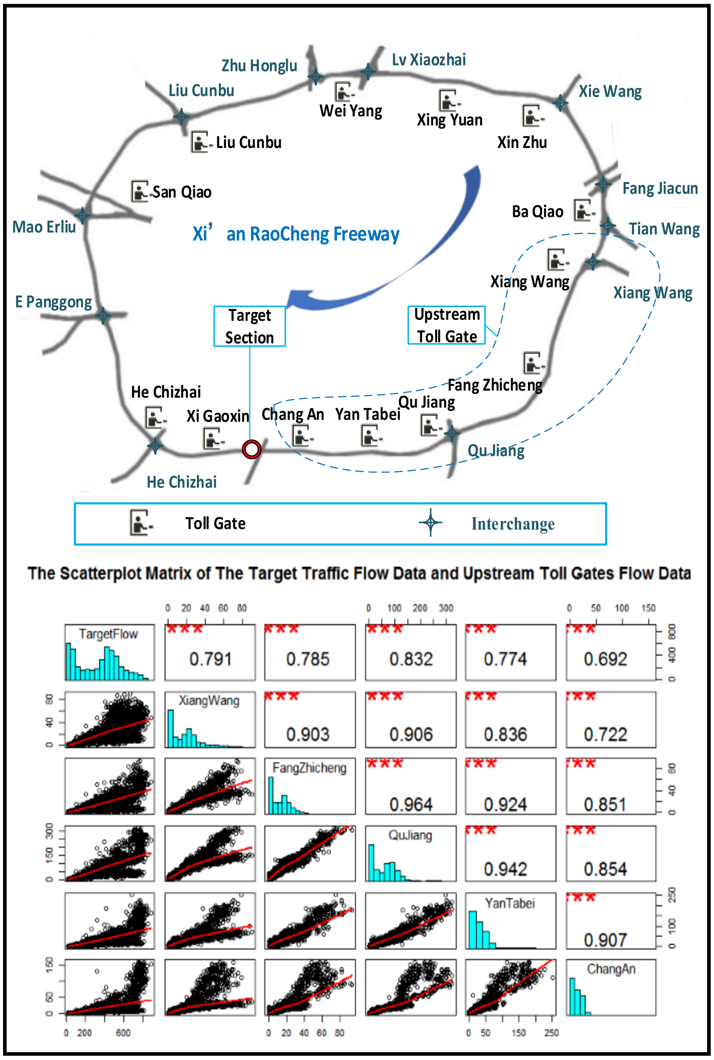

FIGURE 2. The geometric map of the Xi'an RaoCheng freeway in this figure. The location of target section and five upstream toll gates are marked. The correlation analysis between the traffic flow and those upstream toll gates are provided in the scatterplot matrix.

C. LONG SHORT-TERM MEMORY

In traditional neural networks, there are only fully connected layers from input layer to hidden layer or from hidden layer to output layer, but no connections among the nodes in the same layer, which encompass many parameters and fail to utilize time series message. Conventional RNNs are afflicted with vanishing or exploding gradients when the number of time lags is large [25]. LSTM integrated memory units to disentangle vanishing and exploding gradients in conventional RNNs [2].

A typical structure of LSTM cell can be seen in Fig.4. A LSTM cell contains three gates: the input gate, the hidden gate and the output gate. These gates are more effective to determine what information to remove or reserve. The memory units play a significant role in deciding when to forget previous hidden states and iteratively update hidden states than traditional RNNs. The mathematic model of LSTM [2] can be conducted by the equations shown as follows:

$$I_t = \delta(W_i X_t + R_i H_{t-1} + b_i) \tag{3}$$

$$F_t = \delta(W_f X_t + R_f H_{t-1} + b_f) \tag{4}$$

$$O_t = \delta(W_o X_t + R_o H_{t-1} + b_o) \tag{5}$$

$$\widetilde{C}_t = \tanh(W_z X_t + R_z H_{t-1} + b_z) \tag{6}$$

$$C_t = \widetilde{C}_t \odot I_t + C_{t-1} \odot F_t \tag{7}$$

$$H_t = O_t \odot \tanh(C_t) \tag{8}$$

where I_t, F_t and O_t are the output of input gate, hidden gate and output gate, respectively; W_i, W_f, W_o, W_z, R_i, R_f, R_o, R_z are the coefficient matrixes, which connect input and three gates; $\widetilde{C}_t$ stands for the input state; C_t stands for the updated state or cell output; H_t is the hidden layer output; $\delta()$ and

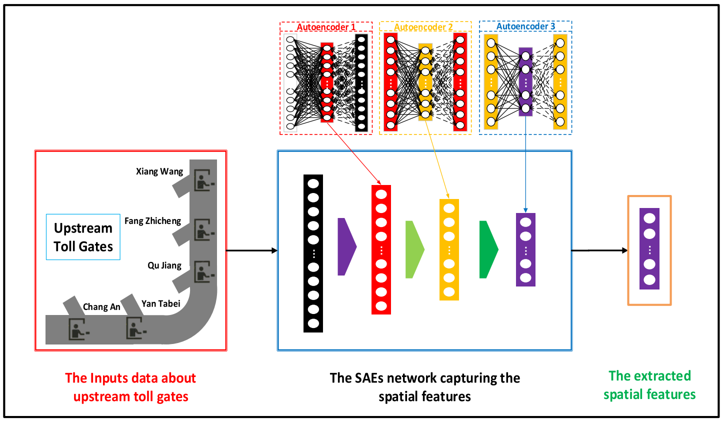

FIGURE 3. The SAEs model is consisted of three parts: (a) The input of network is the data of upstream toll gates; (b) Each layer of network is pre-trained with the greedy layerwise unsupervised learning algorithm; (c) The output of network are the extracted spatial features.

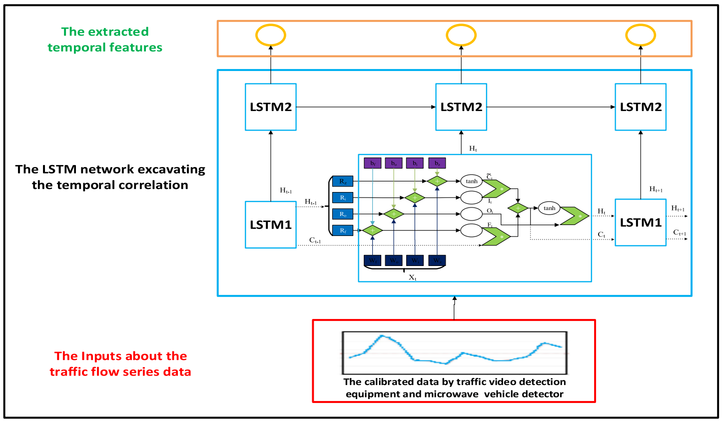

FIGURE 4. The structure of LSTM model. The input of model is the calibrated data by traffic video detection equipment data and microwave vehicle detector data, and the output of the model are the extracted temporal features.

tanh() are the activation function; and the scalar product of two vectors or matrixes is denoted by $\odot$.

D. HYBRID SAEs-LSTM ALGORITHM

The traffic state has a distinct dependency on spatial or temporal information, which means the current traffic state would be affected by the state several minutes earlier or upstream flow. It is hypothesized that the spatial features can be learned by SAEs model and the temporal characterizes can be captured by LSTM in this paper. Based on this hypothesis, we proposed a novel hybrid deep learning model named SAEs-LSTM to forecast traffic flow of urban expressway. To this end, a SAEs model is utilized to reduce the dimension and capture the spatial features of TG data, and a LSTM model is exploited to excavate temporal correlation from the calibrated data by traffic video detection equipment data and microwave vehicle detector data. A graphical illustration of SAEs-LSTM has been shown in Fig. 5. A merge layer takes as input a list of tensors, all of the same shape, and returns a single tensor which has the same shape as input tensor. An adding merge layer, which adds SAEs output to LSTM output as the input layer of regression layers, is used to achieve spatial-temporal features fusion. The regression layers consist of three fully connected layers to predict traffic flow. In this experiment, we merged two tensors into a single tensor. The merged layer can be formulated as:

$$I_r = SAEs_o \oplus LSTM_o \tag{9}$$

where $SAEs_o$, $LSTM_o$ is the output layer of SAEs and LSTM; $\oplus$ denotes the add merge function that add the results of two models; I_r is the merged layer or input layer of regression layers. The output in the ith hidden layer can be written as:

$$H_{ri} = relu(W_{ri}I_{ri} + b_{ri}) \tag{10}$$

where H_{ri}, W_{ri} , I_{ri}, b_{ri} are the output, the weight matrix, the input, the bias of the ith hidden layer; *relu* is the activation function and defined as follows:

$$f(x) = max(0, x) \tag{11}$$

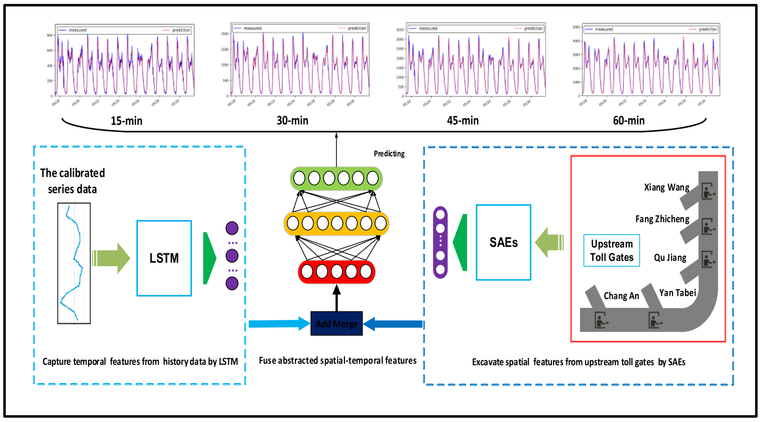

FIGURE 5. The structure of hybrid model, which includes a LSTM model to capture time characteristics from the calibrated series data and a SAEs model to learn space features from upstream toll gates data.

IV. EMPIRICAL STUDY

A. IMPLEMENTATION

In order to build our proposed prediction model, we selected two months of data for this study, in which 47 days of data, from 04/01/2018 to 05/17/2018, are used for training and 14 days of data, from 05/18/2018 to 05/31/2018, are used for testing. The prediction experiments were adopted in a similar procedure to the most common used traffic flow prediction. we aggregated the traffic flow into 15-min, 30-min, 45-min and 60-min intervals for predicting. Although the window size horizon is changing with the change of intervals, it is maintaining 6 hours, which means that 6 hours historical data are used to perform the traffic flow prediction of the next few intervals. For example, the traffic flow at (7:15 AM, 7:30 AM, 7:45 AM, 8:00 AM) are to be predicted if the current time is 7:00 AM when the prediction horizon is 15 mins. The following flow data would be predicted by analogy.

The proposed hybrid model, SAEs-LSTM, was compared with single LSTM and SAEs on multi-source data. The details of our hybrid model on 45-min interval, which are divided into feature extracting layers and regression layers, are listed in Table 2. Besides, slight modifications have been made in the hybrid model and single model on dissimilar sources to make the network achieve the best performance. As an example, the LSTM units in hybrid model are [6, 18, 10] when the input data is CTR data, while they are [6, 20, 10] when the input data only TG+CTR data on 30-min interval. The final effective parameters of hybrid model are achieved by grid searches. The traffic flow as input data are normalized to be between 0 and 1 for training hybrid model and single models, and the output is the true traffic flow. All neural network models are constructed upon Keras 2.2.2 using Tensorflow 1.9.0 for backend.

TABLE 2. The parameter settings on 45-min interval.

Layers	Name	Parameters	Learning rate
Feature Extracting Layers	SAEs	(40,25,20,10)	0.01
	LSTM	(8,18,10)	0.008
Regression Layers	FC1[1]	80	0.008
	Dropout1	0.1	0.008
	FC2[2]	60	0.008
	Dropout2	0.1	0.008
	Output	1	0.008

FC1[1]=$Full\ Connected1$, $FC2^2$=$Full\ Connected2$

B. PERFORMANCE INDEX

In order to evaluate the performances of the proposed models for traffic flow prediction, three performance indexes are adopted to measure the error between prediction and measured data: mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - y_i'| \tag{12}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2} \tag{13}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|\frac{y_i - y_i'}{y_i}| \tag{14}$$

where y_i is the ith actual value, while y_i' is the ith forecast value. From the mathematical formulation (), it can be discovered that MAE and RMSE are more sensitive to raw traffic flow data on different intervals. In order to overcome the sensitivity raw data on different intervals, the input data has been normalized between 0 and 1. And for intuitive comparison, the MAE and RMSE have been converted into the number of vehicles per hour in this paper. Meanwhile, because MAPE based on percentage errors is less affected by intervals, we combined MAE, RMSE with MAPE to evaluate the performance more precisely in different conditions.

TABLE 3. The comparison of different models on various prediction horizon.

Models	Performance index	15-min prediction	30-min prediction	45-min prediction	60-min prediction	Average
SAEs-LSTM	MAE(veh/h)	**104.484**	**113.716**	**128.932**	**138.393**	**121.381**
	RMSE(veh/h)	**152.468**	**168.678**	**189.911**	**200.010**	**177.767**
	MAPE(%)	**10.551**	**9.012**	**8.969**	**9.721**	**9.563**
LSTM	MAE(veh/h)	111.344	130.406	132.580	141.590	128.980
	RMSE(veh/h)	166.004	191.726	191.819	211.839	190.347
	MAPE(%)	11.366	10.923	9.283	10.04	10.403
SAEs	MAE(veh/h)	107.152	125.130	152.505	175.635	140.106
	RMSE(veh/h)	156.928	183.754	219.765	252.401	232.12
	MAPE(%)	10.681	9.071	10.815	11.466	10.508

C. COMPARISON AND ANALYSIS OF DIFFERENT MODELS

In the experiment, we first compared hybrid models with single deep learning algorithms on different time-interval. Table 3 shows the results of proposed SAEs-LSTM model, LSTM model and SAEs model on the intervals of 15-min, 30-min, 45-min, 60-min, respectively. The results of each model are the arithmetic average under dissimilar data sources. The MAE and RMSE in different time-interval have been converted into hourly volume. Fig. 6 shows the MAPE of different models. The MAPE results of each model come from dissimilar data sources(TG+CTR, CTR, TG).

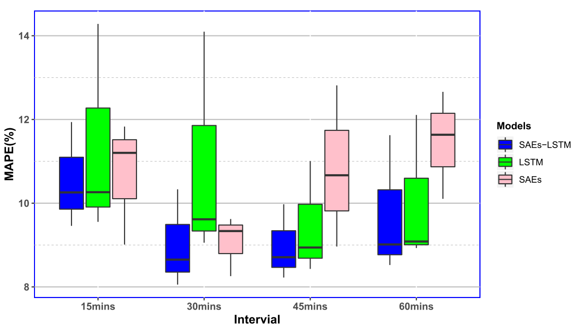

FIGURE 6. The Boxplots of MAPE with different model for traffic flow forecast. The results are obtained by dissimilar data sources.

From Fig. 6, we can see the MAPE in 15-min are worse than other time intervals. We all know that short-term raw data fluctuates greatly than long-term. MAPE represents relative error between true data and prediction data. The more MAPE may be produced by small prediction error on shorter time intervals. Because on the longer time intervals, the larger the denominator of the formula (14) but the numerator changes little, which means that larger MAPE may be accompanied by smaller errors. Table 3 also reflects this fact where the MAPE is lager, but the MAE and RMSE are smaller on 15-min interval than other intervals. The MAE and RMSE are increasing as the prediction time intervals increase, which is similar to the results of previous researches. It can be found that SAEs is than LSTM in shorter time-interval, while LSTM is than it in long time-interval. Meanwhile, from the results in Table 3 and the results plotted in Fig. 6, we can see SAEs-LSTM model performs better than LSTM and SAEs both short-term prediction and long-term prediction. The average MAE decreases by 6.26%, 15.4% and the average RMSE decreases by 7.08%, 14.3% than LSTM and SAEs. However, the MAPE decreases by 8.78%, 9.88%, which seems to be small but means that would produce large error (approximately 351 vehicles, 395 vehicles) on peak hourly volume(approximately 4000 vehicles). In a comprehensive view, the hybrid model, SAEs-LSTM, outperforms other models, with the lowest MAE, RMSE and a MAPE of approximately 9.563%. Therefore, the hybrid model we proposed makes the results more accurate for traffic flow prediction. The next section of the survey was concerned with the effect from dissimilar data sources for traffic flow prediction.

D. COMPARISON AND ANALYSIS OF DIFFERENT DATA SOURCES

In this section, three types of data sources, including the combination of TGs data and the CTR data, TGs data, CTR data, are used to predict traffic volume in terms of four kinds of time-interval. The results of dissimilar data sources on different intervals for traffic flow prediction are listed in Table 4. Similarly, the results of each data source are the arithmetic average on different models, and the MAE and RMSE in different time-interval also have been converted into hourly volume. Fig. 7 shows the MAPE of dissimilar data sources. The MAPE results of each source come from different model(SAE-LSTM, LSTM, SAEs).

It can be seen in Table 4 and Fig.7 that the model with spatiotemporal information outperforms the model with other data sources not only on average but also in each time-interval. The boxplot depicted Fig.7 also shows that the results of model with CTR data are in close proximity to model with TGs data and CTR data, but they fluctuate greatly than the latter data source, which means that the model with spatiotemporal information obtains higher robustness in predicting traffic flow. The average MAE of TGs+CTR data decreases by 14.52%, 23.579% and the average RMSE of TGs+CTR data decreases by 14.078%, 21.719% than CTR data and toll gate data, respectively. Furthermore, the MAPE of TGs+CTR data decreases by 10.014%, 33.151% even

TABLE 4. The comparison of dissimilar data sources on various prediction horizon.

Models	Performance index	15-min prediction	30-min prediction	45-min prediction	60-min prediction	Average
CTR+TG	MAE(veh/h)	**94.588**	**107.190**	**121.637**	**138.538**	**115.488**
	RMSE(veh/h)	**139.644**	**157.582**	**180.281**	**203.055**	**170.141**
	MAPE(%)	**9.341**	**8.456**	**8.54**	**9.185**	**8.881**
CTR	MAE(veh/h)	106.367	125.928	139.733	157.008	132.259
	RMSE(veh/h)	156.951	183.436	205.056	230.927	194.092
	MAPE(%)	10.574	9.200	9.394	9.911	9.770
TG	MAE(veh/h)	122.024	136.132	152.648	160.073	142.719
	RMSE(veh/h)	178.808	203.140	216.157	230.268	207.093
	MAPE(%)	12.683	11.350	11.134	12.131	11.825

CTR $= The\ calibrated\ data\ by\ TVED\ and\ RTMS$, TG $= Toll\ Gate$

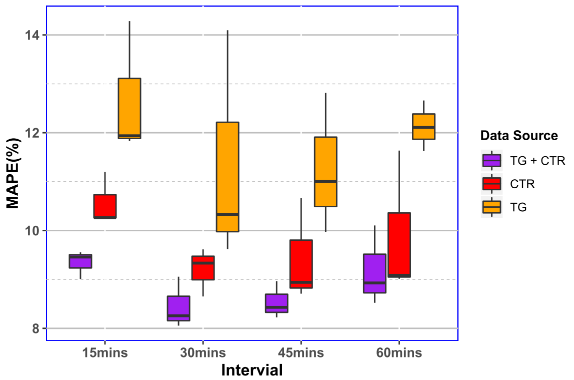

FIGURE 7. The Boxplots of MAPE with dissimilar data sources traffic flow forecast. The results are obtained by different models.TG = "the toll gate data" , CTR = "the calibrated data by TVDE and RTMS".

more than other two kinds of data sources. Specifically, the advantage of the model combining spatial information and temporal information in predicting is more obvious from Fig.9.

E. COMPARISON AND ANALYSIS OF DIFFERENT MODELS AND DATA SOURCES

The circles, triangles and squares in Fig. 9 are used to represent different models: SAEs-LSTM, LSTM and SAEs. Moreover, the color of purple, red and orange in the figure indicates different data sources: TG+CTR data, CTR data and TG data. We have the following findings by comparing different data sources and different models at the same time:

1) Purple circles in Fig. 9 represents the hybrid model based on spatial and temporal information. It is evident from the figure that purple circles are always in the bottom left corner on the time interval of 30, 45 and 60 minutes, which shows that hybrid models with spatiotemporal information produce the minimum error. A similar conclusion that the prediction values presented by red dashed lines are always closer to the actual measured data presented by blue dotted lines can be reached in Fig. 8, which means our proposed models yield the most accurate results for traffic flow prediction.

2) It can also be found that most of purple shapes are in the bottom left corner(the minimum error area) of each interval. The models with TG+CTR data perform better than others with one single data all the time, which means the models with spatiotemporal information always yield the least prediction error for traffic flow prediction. But LSTM model with TG+CTR data shows poor results in longer intervals (45-min, 60-min). This may be caused by the characteristics of LSTM model and the decrease of the number of training set with the increase of time interval.

3) Besides the findings described above, that red circles are always below the orange circles shows the hybrid model with CTR data performs better than it with TG data all the time, which indicates that temporal features contribute more than spatial information for traffic prediction.

4) In addition, the hybrid model with single data source or multiple data sources applied for single model may be transcended by single model based on single data source. For example, hybrid model with CTR data on 45-min and 60-min interval yield more error than LSTM with CTR data and SAEs with multi-source data yield more error than LSTM model with CTR data, which is circled in Fig. 8 by blue lines. But hybrid model based on spatiotemporal information always has lowest errors shown in Fig. 9 by purple circles, which means that proposed model with fusion information can achieve higher prediction accuracy compared with the combination of single model with multi-source data or hybrid model with single data. This method also provides a new way of thinking about both traffic data mining and traffic flow prediction.

V. DISCUSSIONS AND CONCLUSIONS

In this paper, we proposed a novel hybrid model to achieve traffic flow prediction based on the multisource original traffic data which include spatial information and temporal information. The advantages of hybrid model combine two models in consideration of each cons and pros. However, selecting models is worth studying instead of simply using more models. The selection of models should be suitable for the characteristics of the data. In this paper, SAEs can be used to compress data in spatial dimension and train greedy

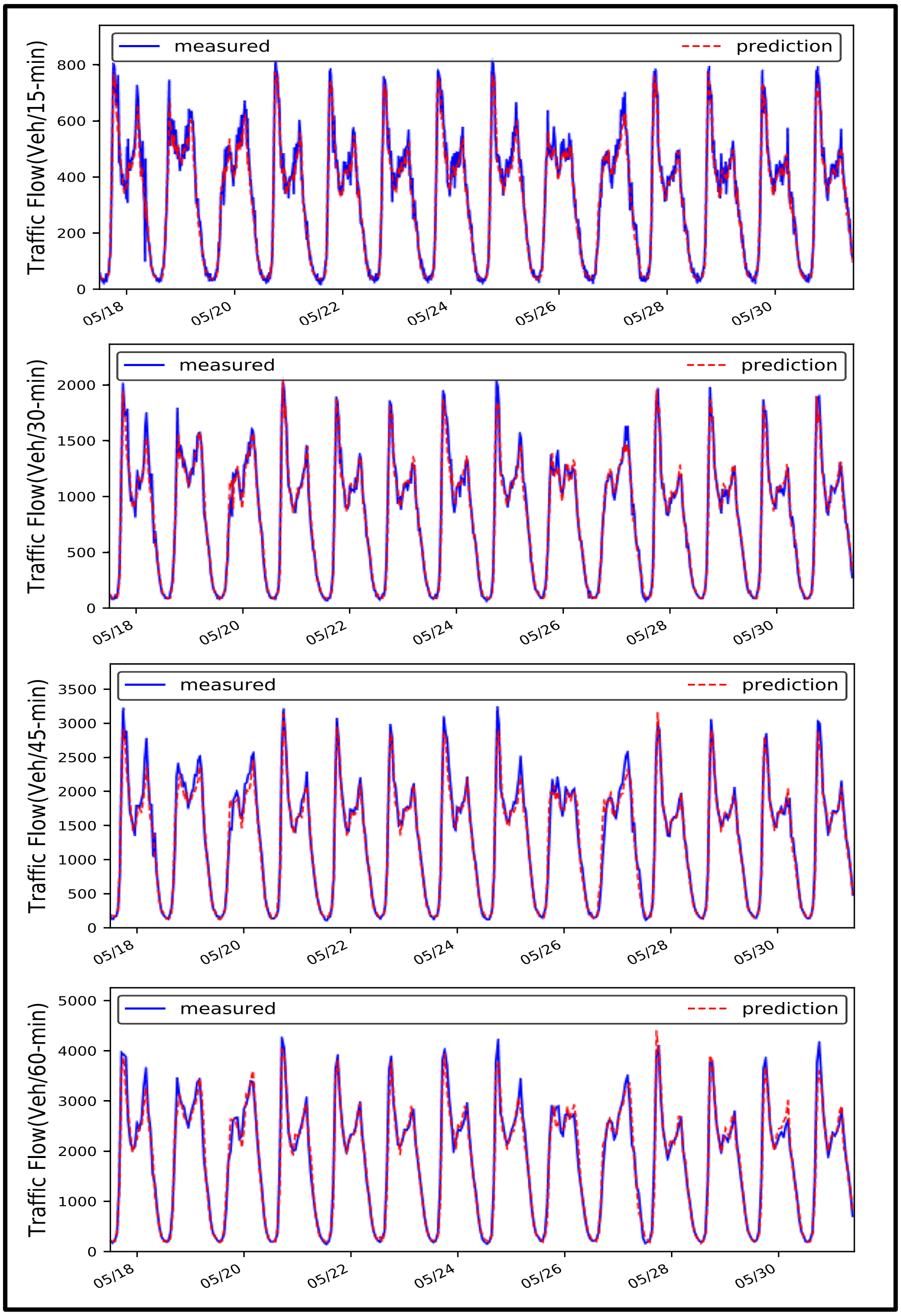

FIGURE 8. 15, 30, 45 and 60 minutes traffic flow forecast for two weeks of hybrid model. The blue dotted lines represent the actual traffic flow and the red dashed lines represent the prediction results.

layerwise with supervised fine tuning. And LSTM is used to tackle data in the temporal dimension. The combination of SAEs and LSTM attained high-dimensional data features than purely used one. In order to evaluate the performance of the proposed hybrid model, a cross-validation of multisource original traffic data and two state-of-the-art models, LSTM and SAEs, were implemented for comparison with the same dataset. The numerical results demonstrate that the SAEs-LSTM hybrid model with multisource original traffic data always outperforms other models with dissimilar data both in accuracy and robustness, which shows the effectiveness of hybrid model for the traffic data forecasting with spatiotemporal data.

Other than combination of models, we have also taken time to investigate the strategy of fused data. Especially in the practical application of the traffic scenario, multiple sources are used to capture and report the road state on time. The forecast of the traffic flow is important both for the road users and administrator. The contribution of the proposed accurate forecasting are listed:

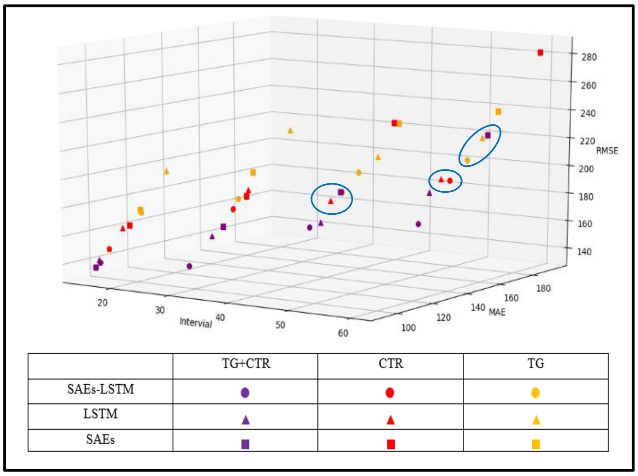

FIGURE 9. **The traffic flow forecast errors MAE and RMSE on 15, 30, 45 and 60 minutes. TG = "the toll Gate data", CTR = "the calibrated data by TVDE and RTMS".**

1) The forecasting future traffic flow volume relies on current traffic flow volume and upstream toll collection data. The prediction traffic volume could be not only the fixed cross-section on the road, but also any cross-section on the road. Those traffic flow data are captured from road that covers all the vehicle driving on the road. The forecasting result is more accurate than that captured from the floating cars.

2) When the emergency happens on the freeway, fast and effective traffic control is extremely important to rescue. Avoiding congestion is one of the most prominent tasks to save life and decrease other influence in the emergency situation. The more precise result could contribute to more effective strategy for reducing the congestion time. The administrator could make strategy according to the future volume on the emergency point from the forecasting model. For example, it is very valuable and helpful for administrator to decide which entrances of upstream toll collection should be shut down. Besides, it is of significance for traffic department that could release the traffic guidance information to avoid the extent congestion.

3) In this paper, we extract five TGs to improve the forecasting. The accuracy of the prediction accuracy maybe further improved if more TGs involved. However, it will cost more computation resource. There is trade-off between the accuracy and the computation time. In this paper, we use the correlation analysis to pick the more related TG. Large-scale data could be solved with the development of computer technology.

In future research, the forecasting on arbitrary cross-section should be carried out to substitute for the current inductive loop detector and other detection equipment. The prediction results can be verified by the video detection equipment. The underlying connection between the spatiotemporal multiple source data would be further identified. For example, it would take more time for farther toll collection to influent on the traffic flow. Moreover, the finegrain vehicle also could be identified and forecasted with more details.

ACKNOWLEDGMENT

The authors appreciate the data provided by Toll Collection Center for Shaanxi Freeway, P. R. China. They would like to express appreciation to Mr. Wenbang Hao, Mr. Wanrong Xu, Mr. Saisai Wang, Miss Wubei Yuan, Miss Yiwen Gao and Miss Zhen Jia for their help to collect data and present work in various aspects.

REFERENCES

[1] L. Li and D. Zhang, "Merging vehicles and lane speed-flow relationship in a work zone," *Sustainability*, vol. 10, no. 7, p. 2210, Jun. 2018.
[2] X. Ma, Z. Tao, Y. Wang, H. Yu, and Y. Wang, "Long short-term memory neural network for traffic speed prediction using remote microwave sensor data," *Transport. Res. C, Emerg. Technol.*, vol. 54, pp. 187–197, May 2015.
[3] P. Wang, L. Li, Y. Jin, and G. Wang, "Detection of unwanted traffic congestion based on existing surveillance system using in freeway via a CNN-architecture TrafficNet," in *Proc. 13th Conf. Ind. Electron. Appl.*, May/Jun. 2018, pp. 1134–1139.
[4] W. Huang, G. Song, H. Hong, and K. Xie, "Deep architecture for traffic flow prediction: Deep belief networks with multitask learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 5, pp. 2191–2201, Oct. 2014.
[5] G. A. Klunder, H. Taale, L. Kester, and S. Hoogendoorn, "The effect of inaccurate traffic data for ramp metering: Comparing loop detectors and cameras using information utility," *IFAC Proc. Volumes*, vol. 47, no. 3, pp. 11318–11325, 2014.
[6] J. Gajda and P. Burnos, "Identification of the spatial impulse response of inductive loop detectors," in *Proc. IEEE Instrum. Meas. Technol. Conf.*, May 2015, pp. 1997–2002.
[7] I. Laña *et al.*, "On the imputation of missing data for road traffic forecasting: New insights and novel techniques," *Transport. Res. C, Emerg. Technol.*, vol. 90, pp. 18–33, May 2018.
[8] X. Ma *et al.*, "LSTM neural network for traffic speed prediction using remote microwave sensor data," *Transport. Res. C, Emerg. Technol.*, vol. 54, pp. 187–197, 2015.
[9] P. Wang *et al.*, "Regional detection of traffic congestion using in a large-scale surveillance system via deep residual TrafficNet," *IEEE Access.*, vol. 6, pp. 68910–68919, 2018, doi: 10.1109/ACCESS.2018.2879809.
[10] B. T. Morris, C. Tran, G. Scora, M. M. Trivedi, and M. J. Barth, "Real-time video-based traffic measurement and visualization system for energy/emissions," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 4, pp. 1667–1678, Dec. 2012.
[11] C. Hu, K. Xie, G. Song, and T. Wu, "Hybrid process neural network based on spatio-temporal similarities for short-term traffic flow prediction," in *Proc. IEEE Conf. Intell. Transp. Syst.*, Oct. 2008, pp. 253–258.
[12] N. G. Polson and V. O. Sokolov, "Deep learning for short-term traffic flow prediction," *Transp. Res. C, Emerg. Technol.*, vol. 79, pp. 1–17, Jun. 2017.
[13] P. Dell'Acqua, F. Bellotti, R. Berta, and A. De Gloria, "Time-aware multivariate nearest neighbor regression methods for traffic flow prediction," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 6, pp. 3393–3402, Dec. 2015.
[14] X. Zhu, Y. Fan, F. Zhang, X. Ye, C. Chen, and H. Yue, "Multiple-factor based sparse urban travel time prediction," *Appl. Sci.*, vol. 8, no. 2, p. 279, 2018.
[15] I. Okutani and Y. J. Stephanedes, "Dynamic prediction of traffic volume through Kalman filtering theory," *Transport. Res. B, Methodol.*, vol. 18, no. 1, pp. 1–11, 1984.
[16] H. Liu *et al.*, "Predicting urban arterial travel time with state-space neural networks and Kalman filters," *Transport Res. Rec.*, no. 1968, pp. 99–108, 2006.
[17] Y. Zhang and Y. Liu, "Traffic forecasting using least squares support vector machines," *Transportmetrica*, vol. 5, no. 3, pp. 193–213, 2009.
[18] M. Levin and Y. D. Tsao, "On forecasting freeway occupancies and volumes," *Transp. Res. Rec.*, no. 773, pp. 47–49, 1980.
[19] M. Van Der Voort, M. Dougherty, and S. Watson, "Combining Kohonen maps with ARIMA time series models to forecast traffic flow," *Transp. Res. C, Emerg. Technol.*, vol. 4, no. 5, pp. 307–318, 1996.

[20] B. L. Smith, B. M. Williams, and R. K. Oswald, "Comparison of parametric and nonparametric models for traffic flow forecasting," *Transp. Res. C, Emerg. Technol.*, vol. 10, no. 4, pp. 303–321, Aug. 2002.
[21] Y. Wu, H. Tan, J. Peter, and B. Shen, "Short-term traffic flow prediction based on multilinear analysis and k-nearest neighbor regression," in *Proc. COTA Int. Conf. Transp. Professionals*, 2015, pp. 556–569.
[22] F. A. Gers, J. Schmidhuber, and F. Cummins, "Learning to forget: Continual prediction with LSTM," *Neural Comput.*, vol. 12, no. 10, pp. 2451–2471, 2000.
[23] A. Graves, N. Jaitly, and A.-R. Mohamed, "Hybrid speech recognition with deep bidirectional LSTM," in *Proc. Autom. Speech Recognit. Understand. (ASRU)*, Olomouc, Czech Republic, 2013, pp. 273–278.
[24] S. H. Fang, Y.-X. Fei, Z. Xu, and Y. Tsao, "Learning transportation modes from smartphone sensors based on deep neural network," *IEEE Sensors*, vol. 17, no. 18, pp. 6111–6118, Sep. 2017.
[25] Z. Zhao *et al.*, "LSTM network: A deep learning approach for short-term traffic forecast," *IET Intell. Transp. Syst.*, vol. 11, no. 2, pp. 68–75, 2017.
[26] Y. Jia, J. Wu, and M. Xu, "Traffic flow prediction with rainfall impact using a deep learning method," *J. Adv. Transp.*, vol. 2017, 2017.
[27] H. Shao and B.-H. Soong, "Traffic flow prediction with long short-term memory networks (LSTMs)," in *Proc. IEEE Region 10 Conf.*, Nov. 2016, pp. 2986–2989.
[28] U. Ali and T. Mahmood, "Using deep learning to predict short term traffic flow: A systematic literature review," in *Proc. Int. Conf. Intell. Transport Syst.*, 2017, pp. 90–101.
[29] Y. Lv, Y. Duan, W. Kang, Z. Li, and F.-Y. Wang, "Traffic flow prediction with big data: A deep learning approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 2, pp. 865–873, Apr. 2015.
[30] W. Bao, J. Yue, and Y. Rao, "A deep learning framework for financial time series using stacked autoencoders and long-short term memory," *PLoS ONE*, vol. 12, no. 7, p. e0180944, 2017.
[31] Y. Duan, Y. Lv, Y.-L. Liu, and F.-Y. Wang, "An efficient realization of deep learning for traffic data imputation," *Transp. Res. Part C, Emerg. Technol.*, vol. 72, pp. 168–181, Nov. 2016.
[32] Y. Duan, Y. Lv, and F.-Y. Wang, "Performance evaluation of the deep learning approach for traffic flow prediction at different times," in *Proc. IEEE Int. Conf. Service Oper. Logistics, Inform.*, Jul. 2016, pp. 223–227.
[33] Y. Wu, H. Tan, L. Qin, B. Ran, and Z. Jiang, "A hybrid deep learning based traffic flow prediction method and its understanding," *Transp. Res. Part C, Emerg. Technol.*, vol. 90, pp. 166–180, May 2018.
[34] M. Leelavathi and D. K. J. Sahana, "An architecture of deep learning method to predict traffic flow in big data," *Int. J. Res. Eng. Technol.*, vol. 5, no. 4, pp. 461–468, 2016.
[35] Y. Liu, Y. Wang, X. Yang, and L. Zhang, "Short-term travel time prediction by deep learning: A comparison of different LSTM-DNN models," in *Proc. IEEE Int. Conf. Intell. Transp. Syst.*, Oct. 2017, pp. 1–8.
[36] H. Yu, Z. Wu, S. Wang, Y. Wang, and X. Ma, "Spatiotemporal recurrent convolutional networks for traffic prediction in transportation networks," *Sensors*, vol. 17, no. 7, p. 1501, Jul. 2017.
[37] Z. Duan, Y. Yang, K. Zhang, Y. Ni, and S. Bajgain, "Improved deep hybrid networks for urban traffic flow prediction using trajectory data," *IEEE Access*, vol. 6, pp. 31820–31827, Jun. 2018.

YINLI JIN received the B.S. degree in computer science, the M.S. degree in transportation information and control, and the Ph.D. degree in transportation planning and management from Chang'an University, China, in 1995, 2003, and 2010, respectively. He was a Visiting Professor with the Transportation Research Center, University of Wisconsin–Milwaukee, USA, from 2012 to 2013. He is currently the Head of the Department of Automation, Chang'an University, and also the Founder and the Director of the Institute for Transportation Systems Engineering Research, Chang'an University. His current research interests include traffic information system, traffic control and management, and intelligent transportation systems.

ERLONG TAN received the B.E. degree in automation from the School of Electric and Control Engineering, Chang'an University, Xi'an, China, in 2017. He is currently pursuing the M.E. degree in control science and engineering with Chang'an University. His current research interests include intelligent transportation systems, information fusion, and deep learning.

LI LI received the B.S. and M.S. degrees in automation from Chang'an University, Xi'an, China, in 2008 and 2011, respectively, and the Ph.D. degree in transportation engineering from Tongji University, Shanghai, China, in 2017. He is currently an Assistant Professor with the School of Electrical and Control Engineering, Chang'an University. His research interests include intelligent transportation systems, driver behavior, and traffic flow.

GUIPING WANG received the B.E. degree in automation from Xi'an Jiaotong University, the M.S. degree in control theory and control engineering from Huazhong Technological University, China, and the Ph.D. degree in transportation engineering from Chang'an University. He is currently a Professor and the Head of the School of Electronics and Control Engineering, Chang'an University. His current research interests include management of freeway, traffic control, and intelligent transportation systems.

JUN WANG received the B.E. degree in computer science from Northwestern Polytechnical University in 1997 and the M.S. degree in traffic and transportation engineering from Chang'an University, Xi'an, China, in 2008. He is currently a Senior Engineer and the Director of the Toll Collection Center for Shaanxi Freeway. His current research interests include management of freeway, traffic control, and intelligent transportation systems.

PING WANG (M'11) received the B.S. degree in automation from Shandong University, China, in 2004, the M.S. degree in control theory and control engineering from Shanghai Jiao Tong University, China, in 2007, and the Ph.D. degree in intelligent robotics from Nanyang Technological University, Singapore, in 2011. She was a Post-Doctoral Fellow with an international collaboration joint lab at Loughborough University, U.K., and Nanyang Technological University, Singapore, for three years. She joined the Institute for Transportation Systems Engineering Research, Chang'an University, China, as an Associate Professor. Her current research interests include the applications of control algorithm, artificial intelligence, and intelligent transportation systems.