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Forecasting Traffic Volume at a Designated Cross-Section Location on a Freeway From Large-Regional Toll Collection Data

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ABSTRACT Both road users and administrators are keen to know the traffic volume at the arbitrary point on the road network. In China, charging systems have been fully established in closed large-regional freeway networks. They have accumulated massive amounts of toll collection data and provided a possible method to forecast unknown traffic volume at any designated cross-section located on a freeway. A systematic method is proposed to derive the traffic volume step-by-step. First, the average traveling speed is obtained for each vehicle on its shortest path. Then, the traveling time is estimated in each road segment. Finally, the historical traffic volume is derived at the designated cross-section. To make the obtained traffic volume data more practical, a deep learning-based autoencoder is used for forecasting the traffic volume and evaluating its prediction accuracy. All these proposed methods are evaluated with a collection of toll data for one month covering more than 5000 km of freeway under a centralized regional charging system. One location is randomly selected as the designated cross section at 2 km from the upstream toll gate on a road segment of the Xi'an ring. The experimental results show the effectiveness and satisfactory accuracy of predicting the traffic volume in the designated cross-section compared with the data captured by the traffic video detection equipment. Rapid and successful prediction from available toll collection data may provide a practical method for deriving the traffic information without installing any additional regularly maintained detectors and equipment on the freeway.

INDEX TERMS Closed regional charging system, cross-section on freeway, toll collection data, traffic volume prediction.

I. INTRODUCTION

To efficiently use a common transportation infrastructure with limited capacity, it is important to forecast the traffic volume to avoid traffic congestion and queueing phenomena [1], [2]. With the rapidly increasing number of vehicles, these problems are even more prominent, leading to the rapid degradation of partial infrastructure and increased environmental pollution. One of the most commonly used methods to obtain traffic volume in practice is manually counting the number of vehicles from onsite observations or surveillance video systems, which are extremely labor-intensive and time-consuming [3]. Deducing traffic information obtained from floating cars is another way to forecast the overall traffic volume [4]. Considering the vast region of freeways, there are few floating cars report traffic conditions while traveling on the freeways. Furthermore, vehicle detectors (VDs)/inductive loop detectors, radars and other equipment are usually installed on the freeway to detect traffic conditions [5]–[7]. Taking VDs as an example, it could capture the traffic volume, traveling speed and occupancy

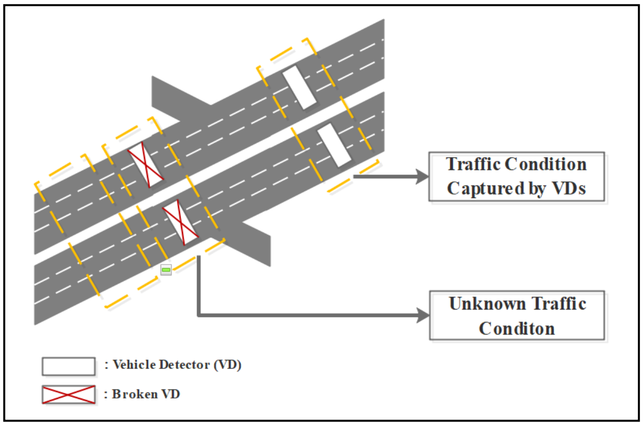

FIGURE 1. Detection of traffic conditions in a road segment: traffic conditions can be captured when a vehicle detector (VD) is installed on a traffic cross-sectional position. Traffic conditions at other positions without VDs or with broken VDs are unknown.

of the fixed location. Several problems have emerged with the years of accumulated data. First, the time required for frequent maintenance and regular updating of broken VDs is always insufficient considering the large number of devices installed on the freeways [8], [9]. Second, the accuracy of VDs is sometimes not high enough, especially in the case of high vehicle density. Moreover, VDs are placed at fixed locations to report traffic volume on those specific locations, not arbitrary locations, as indicated in [10, Fig. 1]. That is, the traffic condition can be captured only with VDs installed on a specific cross-sectional position. It is difficult to recognize traffic conditions in other positions without installed VDs and where VDs is broken. However, it is important to know those traffic conditions for both road administrators and road users to avoid unexpected queuing that randomly occurs in arbitrary locations. Many researchers have attempted to derive traffic volume to reduce the congestion and eventually contribute to the development of the intelligent transport system (ITS).

To estimate traffic information on an arbitrary cross-section on a freeway without installed VDs, other related data sources are employed, including data obtained from radars, cameras, traffic video detection equipment (TVDE), mobile GPS, crowdsourcing, and social media [11], [12]. In China, the charging system fully covers all operating freeways. The charging system provides an alternative way to derive the traffic conditions as the charging data contains time and location of each vehicle [13]. Within the charging system, both electronic toll collection (ETC) and manual toll collection (MTC) [14]–[16] are available to reflect traffic conditions with massive data accumulated every day. With the rapid development of big data analysis, the underlying correlation between toll collection data and traffic flow might possibly be extracted. However, this is not easy to achieve. To estimate traffic volume on a specific point on any cross-section, considerably more specified information is needed. One of the unsolved problems is that toll collection data link to the overall traveling speed for individual vehicles. The overall traveling speed cannot represent a specified speed passing through a designated point. Therefore, the specific time for a vehicle to arrive at a designated position remains unknown. Neither does the traffic volume at a designated point.

In this paper, we propose a historical traffic volume deriving method. Herein, the overall traveling speed for every individual vehicle is utilized to estimate the traveling time in each road segment of each vehicle. Then the specific time for each vehicle to arrive at a designated position can be acquired, which could be used to estimate the traffic volume of the designated position. This method considers the spatial and temporal correlations of the historical traffic flow data. In order to build up plans to avoid unexpected road congestion timely for road administrators and road uses. This research extracts the inherent features hidden in the massive historical traffic volume data with the stacked autoencoder (SAE) model, which is a deep-learning-based method to forecast the traffic volume at a designated cross-section.

The contributions of this work are listed as:

Firstly, we proposed a systematic method to derive the traffic volume on a designated cross-sectional position from toll collection data. It provides a possible way to obtain the traffic flow based on computation. The high-cost spending on measuring equipment might be saved in the future.

Secondly, database is established from the freeway current on service in China. The spatial and temporal correlation between traffic volume and large regional toll collection data are explored via successful estimation of traveling speed, traveling time and other traffic information. Successfully using daily operating data is one of the contributions in consideration the variety and huge amount of data.

Finally, we show the effectiveness of our deducing and prediction method could be used with fast processing time and high accuracy to meet the standard for the practical application. This algorithm has potential values to be extent.

The rest of the paper is organized as follows: in Section II, we review the related work on traffic volume acquiring method and traffic volume prediction. Section III introduces the models and methods proposed in this paper. Section IV provides details of the experimental results and the performance evaluation of the proposed model. Section V presents the conclusions of the paper.

II. RELATED WORK

With the accumulation of the traffic data, many researchers worked on estimation of traffic volume with high accuracy. It is possible that expensive detection equipment might be replaced by a low-cost economic computational model. The costs, time and manpower can be saved, including installation, repair and regular maintenance for the detection equipment.

From toll collection records, massive useful information can be obtained, including traveling time, traveling speed, travel distance, and the origin and destination (OD) of each vehicle [17]. Few studies have established deducing models to obtain the traffic volume from toll collection records in a closed regional charging system. Zhang *et al*. [18] proposed and proved an assumption that the traffic volume of the current road segment has close correlations with the traffic volume of its upstream toll gates. Wu *et al.* [19] generated and forecasted road status based on valid information from toll collection data. Large-scale traffic datasets play an important role to improve traffic conditions or analyze the traveling [20], [21]. In freeway scenarios considering the very large amount of related big data, successful modeling between toll collection data and cross-section traffic flow can be studied based on analysis of their underlying correlations.

To solve this problem, many researchers have investigated the origin/destination (OD) pair and identified more information. Although an exact and perfect deducing model may not exist, a practice assumption is proposed because vehicles passing through similar geographical features, including various road curvatures and road alignments, these vehicles might share similar driving behavior. In addition to spatial information, temporal and weather changes also affect vehicle speed. Under this assumption, common driving behavior in divided road segments sharing similar behavior of individual vehicles might be derived from the stream traveling speed [22]. For example, it is assumed that all vehicles slow down when they take turns on an uphill road. These potential correlations contribute to the prediction of the traveling speed in a designated cross-section, which is an interesting topic deserving further investigation.

To further improve the intelligence of traffic control, predictions for designated cross-section traffic flow are explored. Classic models such as the time series model, the Kalman filtering model, the Markov model, and the support vector machines (SVM) model have been utilized in this area. Among these models, the time series model, such as the autoregressive integrated moving average (ARIMA), focuses on extracting the time patterns of the historical data. By summarizing the rules between the relevant data, the Markov model can determine the state of the road at a future time. Combining linear state equations, the Kalman filtering model can obtain an optimal estimate of the road state [23]–[25]. Based on the SVM method, Su *et al.* [26] found that the analysis model is superior to forecast approaches in accuracy and much more effective. Most of these traditional methods depend on inducing the characteristics of historical data to assume future traffic volume.

As a group of deep nonlinear topology models, deep learning methods can be used as a substitute for the classic linear method. Researchers concluded that by extracting the features hidden in the data, vital information could be obtained. Successful modeling of the irregular data of the real world could improve the prediction accuracy [11], [27]. For example, Kong *et al.* [28] analyzed human travel behavior with SubBus approach, extracted four features of travel behaviors to forecast travel requirements. Yi *et al.* [29] used a deep neural network (DNN) model to forecast real-time traffic volume in 5-minute intervals, the accuracy rate reached 99%, but the scale of the data was small. The recurrent neural network (RNN) [30] is another method widely used in traffic volume prediction. It can save the features hidden in the data to predict temporal-spatial traffic volume with memory cells. Based on the RNN model, the long short-term memory network (LSTM) has an improved structure. There are input gates, output gates, and forget gates [31], these gates and memory cells comprise the model so that it can learn the relationship of long-term dependencies among the input data [32]. The gated recurrent unit (GRU) model, which is a variant of the LSTM model, is considered to perform better than LSTM in the fields of traffic volume prediction [33]. All these deep structures and multiple layers of neural networks have shown successful performance in extracting the internal features of data. The potential features and patterns of historical data can be found, which can greatly improve the accuracy of prediction. One of the successful applications of the deep learning model is the stacked autoencoder (SAE) model, which has a deep structure for prediction and has been presented for good prediction of traffic flow [14], [34].

III. METHODOLOGY

The methodology section mainly includes two parts. 1. Present the algorithm to derive the historical local traffic volume from large regional toll collection data. 2. Introduce the SAE model to forecast the traffic volume.

A. DERIVING LOCAL TRAFFIC VOLUME FROM LARGE REGIONAL TOLL COLLECTION DATA

With the useful fields of the existing freeway toll collection data and considering the speed requirements of different road segments for the traveling vehicles, the algorithm processes the toll collection data in the time and spatial domains simultaneously to acquire the historical traffic volume at the arbitrarily designated cross-section. In our study, the traffic volume finally obtained is counted in 5-minute intervals.

1) AVERAGE THE TRAVELING SPEED IN THE SHORTEST PATH FOR INDIVIDUAL VEHICLES FROM THE TOLL COLLECTION DATA

From the toll collection data, the entry time, exit time, entry toll gate and exit toll gate of each individual vehicle can be obtained. Based on the entry toll gate and the exit toll gate information, the Dijkstra shortest path algorithm can be employed to calculate the shortest path and the corresponding travel distance of each record. The traveling time of each vehicle can also be obtained from the entry time and the exit time. Then, the average traveling speed in the shortest path of an individual vehicle can be calculated as:

$$\bar{V}(j) = L(j)/(T'' - T') \tag{1}$$

where T'' is the exit time of vehicle j. T' is the entry time of vehicle j. $L(j)$ is the travel distance on the shortest path of vehicle j. $\bar{V}(j)$ is the average traveling speed of vehicle j.

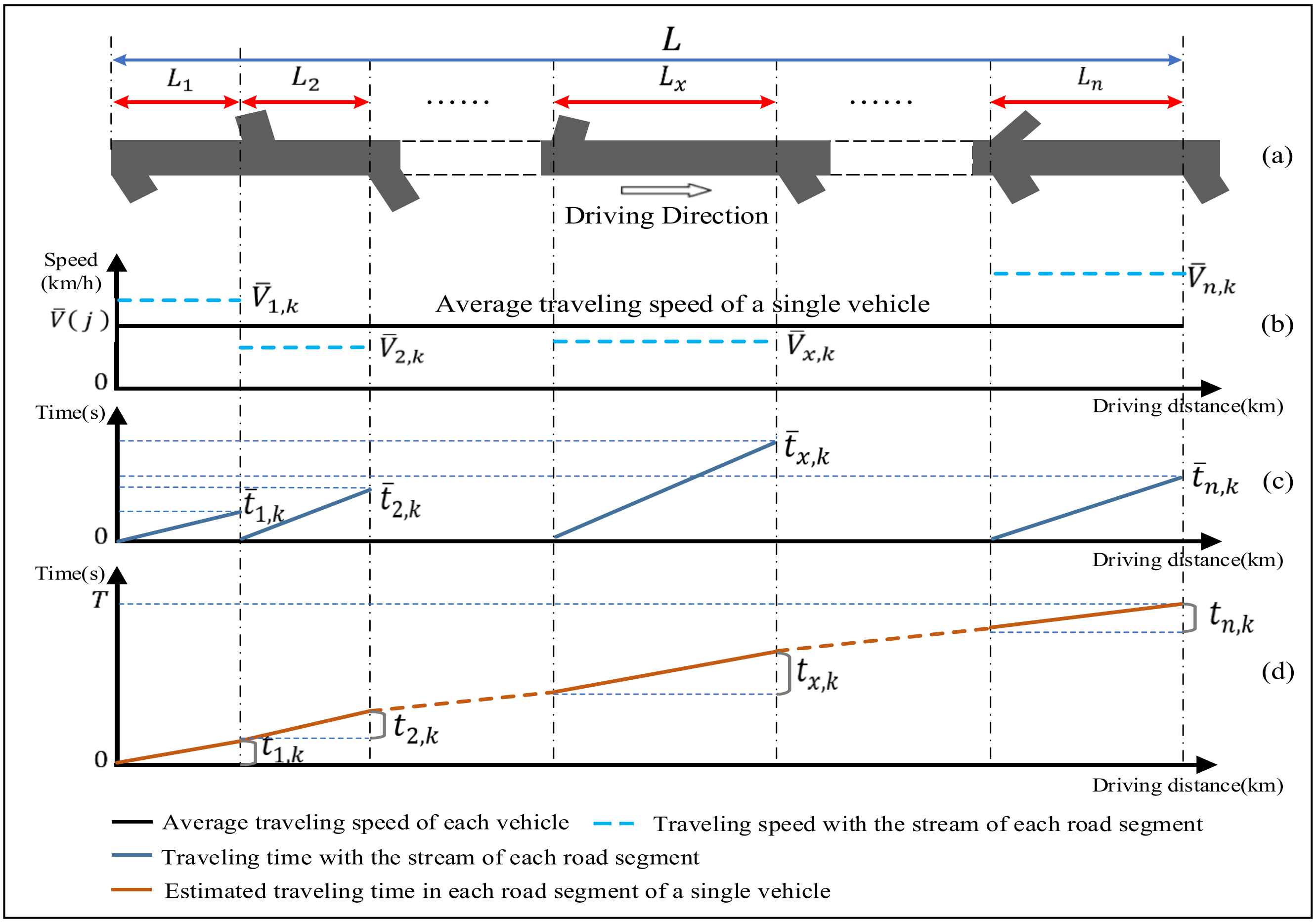

FIGURE 2. The sketch map showing the process of acquiring the estimated traveling time in every road segment. (a). Freeway structure; (b). The average traveling speed of each vehicle and traveling speed with vehicle stream of each road segment; (c). Traveling time with the stream of each road segment; (d). Estimated traveling time in each road segment of each vehicle.

2) ESTIMATE THE TRAVELING TIME IN EVERY ROAD SEGMENT CLOSE TO THE REAL SITUATION

With the overall traveling time for each vehicle, we try to estimate the traveling time on each road segment for each vehicle on its shortest path. Assuming that each vehicle travels along the shortest path with the overall average speed, the traveling time in each road segment is roughly obtained, which may deviate from the real situation. For an individual vehicle, the average traveling speed remains unchanged across its entire shortest travel path. However, due to the different circumstances of different road segments (e.g., road curvature and road alignment, weather changes, different types of vehicles, etc.), each segment has a certain stream traveling speed for different types of vehicles. Therefore, we introduce the traveling speed with the stream and the traveling time with the stream of each road segment as reference values. This part introduces the method to compensate for the traveling time in every road segment approach to the real situation of the individual vehicle. According to standard (JTG B01-2014) [35], the vehicle type of each toll collection record is classified based on the axles. Passenger cars and two-axle trucks are classified as small-sized vehicles. Buses and three or four axle trucks are medium-sized vehicles. Five or more axle vehicles are large-sized vehicles.

The overall idea for the procedure is presented in Figure 2.

For each road segment in the network, we select all the k-type vehicles whose shortest travel path includes the i-th road segment, and statistically calculate the average traveling speed of these vehicles, and then obtain the traveling speed with the stream of the i-th road segment for k-type vehicles. Then, with the length of the road segment, the traveling time with the stream of the i-th road segment can also be calculated. The relationship between the traveling speed with the stream and the traveling time with the stream can be calculated as:

$$\bar{V}_{i,k} = \sum\nolimits_{j=1}^{m_k} \bar{V}(j)/m_k \tag{2}$$

$$\bar{t}_{i,k} = L_i/\bar{V}_{i,k} \tag{3}$$

where $\bar{V}(j)$ is the average traveling speed of vehicle j, m_k is the number of the toll collection data records in which vehicle type is k and the travel path includes the i-th road segment, L_i, $\bar{V}_{i,k}$, $\bar{t}_{i,k}$ represents the length, the traveling speed with the stream and the traveling time with the stream of the i-th road segment obtained from the k-type vehicle, separately.

From the shortest travel path of the individual vehicle, it can be determined which road segment the vehicle passes through, and the traveling time with the stream of these segments can also be acquired. Based on the actual traveling time from the entry gate to the exit gate of each vehicle, we can estimate the traveling time in every road segment that closes to the real situation, which can be denoted as:

$$t_{i,k} = T * (\bar{t}_{i,k} / \sum\nolimits_{i=1}^{n} \bar{t}_{i,k}) \tag{4}$$

where $t_{i,k}$ is the estimated traveling time in the i-th road segment of each vehicle, k represents the type of vehicle, and T is the traveling time from the entry toll gate to the exit toll gate of each vehicle. n is the number of road segments from the entry toll gate to the exit toll gate of each vehicle. The calculated variables $\bar{V}_{\mathrm{i,k}}$ and $\mathrm{t_{i,k}}$ are updated once a month based on the toll collection data acquired each month.

3) DERIVE LOCAL TRAFFIC VOLUME AT DESIGNATED CROSS-SECTION

Due to the road alignment of the freeways, the toll gates are connected in sequence across the freeways. Once a vehicle passes the upstream toll gate and the downstream toll gate of the designated cross-section, it will pass the designated cross-section unavoidably and can be counted in the traffic volume of the designated cross-section. For each vehicle, the estimated traveling time in each road segment on the shortest travel path is already known; therefore, the specific time when the vehicle arrives at the designated cross-section can be obtained.

Assuming that vehicle j enters the freeway at time T' and exits the freeway at time T'', the distance between the cross-section A and its upstream toll gate is also known; then, we can acquire the time that vehicle j spent from the entry toll gate to the designated cross-section A:

$$\Delta t_A = \sum\nolimits_{i=1}^{x-1} t_{i,k} + t_x * (L_{Dis}/L_x) \tag{5}$$

where Δt_A is the traveling time from the entry toll gate to the designated cross-section A. x is the number of road segments from the entry toll gate to the designated cross-section. t_i is the estimated traveling time in the x-th road segment. L_{Dis} and L_x is the distance between the upstream toll gate at the x-th road segment and the designated cross-section, the length of the x-th road segment, respectively.

The estimated time for each vehicle arriving at the designated cross-section can be obtained as:

$$T_A = T' + \Delta t_A \tag{6}$$

where T_A is the estimated time when a single vehicle arrives at the designated cross-section, and $T^{'}$ is the entry time of each vehicle.

Then, all the records can be aggregated in the required time interval. In this paper, the volume of the cross-section is counted in 5-minute interval, and it can be integrated into 15-minute or more if needed. The procedure for deriving the local traffic volume from large regional toll collection data is summarized as follows:

1) For each record of the original toll collection data, calculate the shortest path, e.g., $(Seg_1 - Seg_2 - \ldots - Seg_n)$, the travel distance l, the traveling time T and the average traveling speed $\bar{V}(j)$.
2) For each road segment in the network, select the toll collection records for which travel path includes this segment and the vehicle type is k, calculate the number of these records denoted as m. Calculate the basic information of the road segment, $\bar{V}_{i,k}, \bar{t}_{i,k}$.
3) Select the toll collection records for which the travel path includes the designated cross-section. For each record, determine the vehicle type, and sum the traveling time with the stream of each segment in the entire travel path $\sum_{i=1}^{n} \bar{t}_{i,k}$. Calculate the estimated traveling time the vehicle spent on the i-th section $t_{i,k}$, the traveling time from the entry toll gate to the designated cross-section of each record Δt_A, then the estimated arrival time of each record T_A.
4) Obtain the arrival time of each individual vehicle. Aggregate the number of these vehicles at 5-minute intervals and obtain the traffic volume.

B. FORECASTING TRAFFIC VOLUME AT THE DESIGNATED CROSS-SECTION

In this section, the proposed SAE model, which consists of layers of autoencoders with deep learning-based structures, is presented.

1) AUTOENCODER

The SAE utilizes each autoencoder as a single unit and stacks them together to create a deep network. For the autoencoders, each autoencoder has a three-layer structure, and the input layer needs to be reconstructed. The first layer is the input layer, and the last layer is the reconstruction layer. Both have K units. The hidden layer is used to extract the data features by inputting a set of data $\{x_1^{(l)}, x_2^{(l)}, \ldots, x_n^{(l)}\}$, where $x_i^{(l)} \in R^D$ represents the unit i of layer l. After the nonlinear operation of an autoencoder, the features among the input data can be obtained in the hidden layers and represented as $a\left(x_i^{(l)}\right)$, which can be denoted as the encoding process. In the nonlinear operations, the autoencoder will decode $a\left(x_i^{(l)}\right)$ and output the reconstruction $x_i^{(l)\prime}$, which refers to the decoding process. The formulas are as follows:

$$a(x) = f(\boldsymbol{W_1} x + b_1) \tag{7}$$

$$x' = g(\boldsymbol{W_2} a(x) + b_2) \tag{8}$$

where $\boldsymbol{W_1}$ and $\boldsymbol{W_2}$ are the encoding matrix and the decoding matrix, respectively, which are the weight matrixes of each autoencoder; b_1 and b_2 are the encoding and decoding bias vectors; $f(x)$ and $g(x)$ are the activation functions used in the neural network. In this paper, both the encoding process and

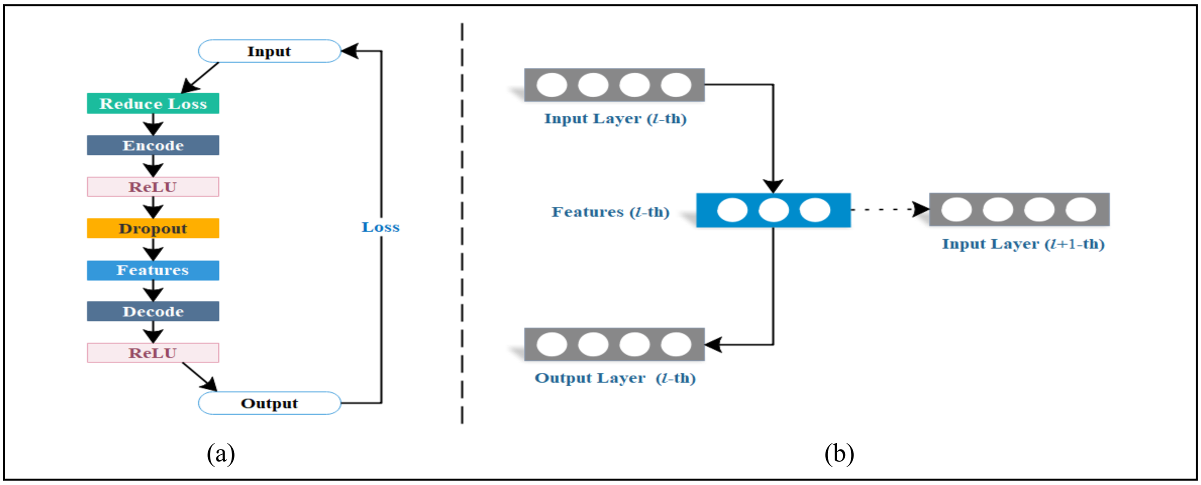

FIGURE 3. **The principle and structure of an autoencoder. (a). The principle of an autoencoder; (b). The structure of an autoencoder.**

the decoding process adopts a rectified linear unit function max (0, x).

Additionally, the reconstruction error is the main parameter for evaluating performance. Here, we define the model variable, denoted as θ, as follows:

$$\theta = arg_{\theta} minL\left(x, z\right) = arg_{\theta} min 1/2 \sum\nolimits_{i=1}^{n} \left\| x_i' - x_i \right\| \tag{9}$$

Usually, nonlinear autoencoders may have a larger number of hidden layer units than the input layer units, which leads to a serious problem that the autoencoder may potentially learn the identity function or simply copy the input data as output, causing the features extracted from the model to be useless. We adopt the "dropout" method after the encoding procedure. By randomly removing a unit, along with the units it linked with temporarily, we can obtain a "thinned" network [36]. Different dropout values may also affect the function of the model. Figure 3 shows the principle and structure of a single autoencoder.

2) SAE MODEL AND ITS FINE-TUNING PROCESSING

A model with a deep learning method usually has more than 3 layers. The number of layers and the number of nodes in each layer influence the predictive results of the model. The SAE model is a structure that stacks autoencoders layer by layer. Each layer is an autoencoder that encodes and decodes data. The input layer passes the data to the 1st hidden layer, then the hidden layer extracts the features through the encoding operation and passes them to the 2nd hidden layer, while the reconstructed output is removed from the network. The following hidden layers perform the same operation until the last hidden layer is reached. Meanwhile, each layer is pre-trained with the greedy layerwise unsupervised learning algorithm [37] to optimize the weights of the layer. When the pretraining process is completed, the output of the last hidden layer is taken as input, and the parameters of the model are fine-tuned via the back propagation (BP) algorithm.

3) INDEX OF PERFORMANCE

To evaluate the prediction error of the SAE model and to compare other prediction models at the end of the research, the commonly used performance indexes are the mean absolute error (MAE), the mean relative error (MRE), and the root-mean-square error (RMSE) to evaluate the error between the predicted and actual values of the model.

$$MAE = \frac{1}{n} \sum\nolimits_{i=1}^{n} |x_i - x_i'| \tag{10}$$

where x_i is the observed data, and $x_i{}'$ is the predicted data. Because the MAE value can reflect the actual situation of prediction error, this paper chooses the MAE value to evaluate the results of different models.

The overall proposed method is illustrated in Figure 4. We first collect the historical toll collection records from every toll gate in a large regional scale around the designated road cross-section. Most of the passing vehicle through the cross-sectional position are reflected in the toll collection data in a large-scaled region around. The traffic volume deriving model are then used to estimate the traffic information on the road and traffic volume on the cross section within the road. Then, we obtain the forecasted traffic volume at different time intervals by using the advantages of the SAE model based on the historical data.

IV. RESULT AND DISCUSSION

A. DATA DESCRIPTION

In this study, the original toll collection data were collected from all the freeway toll gates in Shaanxi province, China. The total mileage of the freeway in Shaanxi province reached 5386 kilometers as of 2018. This paper selects the Shaanxi Freeway network as a closed regional charging system. The collection time of the toll collection data is from January 2018 to April 2018. The cross-section in the middle of the road segment from the Xigaoxin toll gate to the Chang'an toll gate, which belongs to the city ring

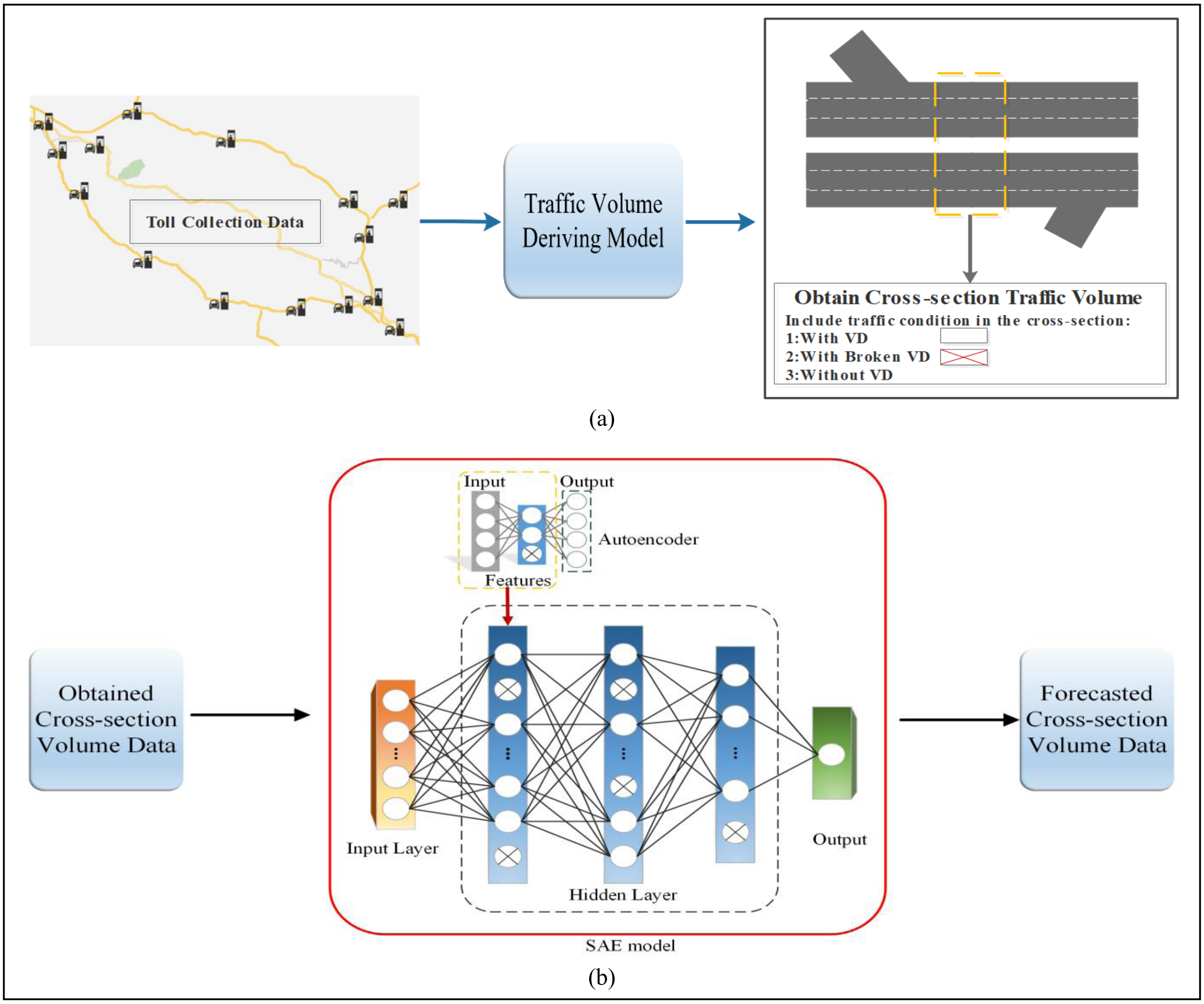

FIGURE 4. **The process of obtaining the historical designated cross-section traffic volume and forecasting the designated cross-section volume. (a). Obtain cross-section traffic volume from toll collection data; (b). Forecast cross-section volume data with SAE model.**

way in Xi'an, Shaanxi, China, is chosen as the designated cross-section because the traffic volume of this cross-section is large enough to meet the requirements of the basic research. In addition, the designated cross-section has relatively large traffic flow and tidal characteristics of the traffic volume as a city ring. The distance from the designated cross-section to the upstream toll gate is 2 km.

The time intervals of the traffic volume data obtained from the deriving algorithm is 5 minutes, 15 minutes, 30 minutes and 60 minutes. The traffic volume data of the first three months are selected as the training set, while the data of the last month are selected as the test set used in the proposed SAE method. Figure 5 shows the description of the data.

B. EXPERIMENTAL SETUP

The experiments are carried out using an Intel i5-3210 MB 2∗2.5 GHz CPU, and 4 GB memory. The next part mainly includes two parts. The first part exhibits and analyzes the results obtained from the procedure of deriving the historical local traffic volume from the toll collection data. The second part analyzes the forecast results of the designated cross-section at different time intervals. Based on the historical traffic volume, we compared the SAE model presented in this paper with the DNN model, LSTM model, DBN model, and SVM model to evaluate the prediction performance.

C. ESTIMATING TRAVELING TIME IN THE ROAD SEGMENTS AND TRAFFIC VOLUME IN ANY DESIGNATED CROSS-SECTION

In this section, to demonstrate the traveling speed with the stream and the traveling time with the stream of each road segment, as well as the estimated traveling time in each road randomly selected three vehicles that entered the city ringway from the Sanqiao toll gate and exited from the Chang'an

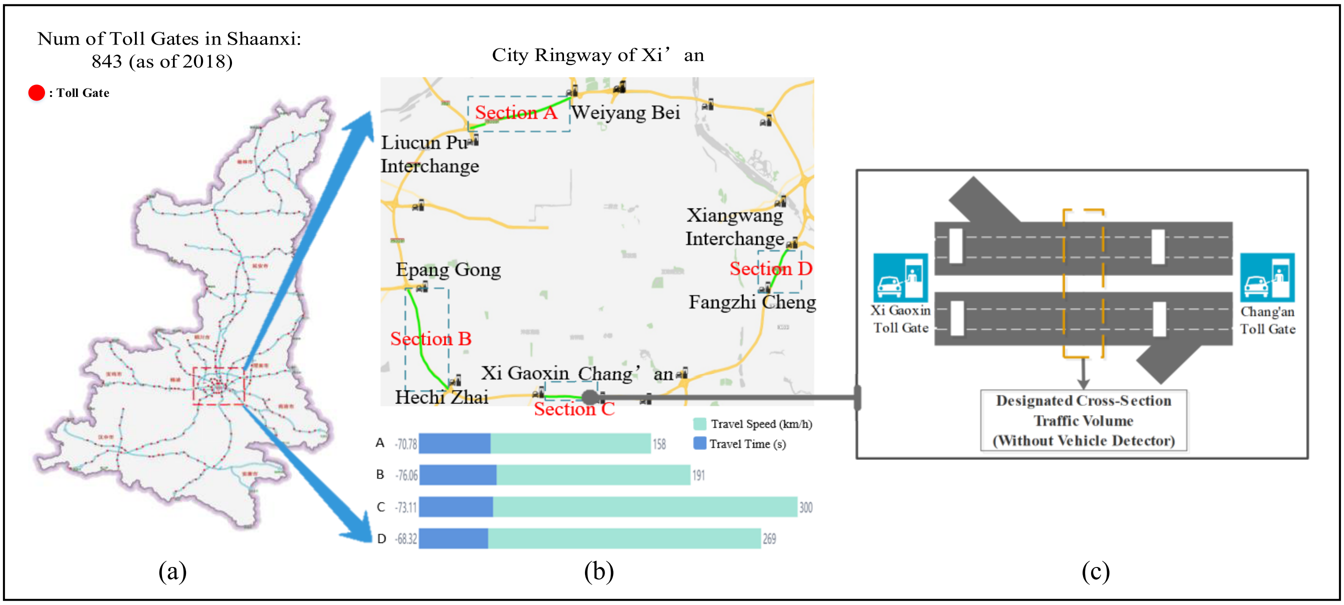

FIGURE 5. **Data description (a). Toll collection data from the whole province; (b). Basic attributes of some cross-sections on the city ringway in Xi'an; (c). Obtained traffic volume at the designated cross-section.**

toll gate as samples from the toll collection data. The size of the three vehicles are representative of small, medium and large vehicles. Their driving times on the freeways are between 7:30 am and 8:00 am, and the driving path also includes the designated cross-section, which is in the road segment from the Xigaoxin toll gate to the Chang'an toll gate. As shown in Figure 6(a), the length of each road segment on the entire travel path varies from 2.4 km to 7.0 km. Figure 6(b) shows the average traveling speed of the three samples on the entire travel path, the small-sized vehicle has the highest value up to 99.69 km/h, the value of the medium-sized vehicle is 77.95 km/h, and the large-sized vehicle has the smallest value, 59.41 km/h. This is consistent with the conclusion that the speed of the small-sized vehicle is faster than that of the large-sized vehicle on the freeway. Using the traveling speed with the stream in each road segment proposed in this paper instead of the overall average traveling speed can be a better approach in real situations. By processing the small-sized vehicle data, the values of the traveling speed with the stream in each road segment are distributed in the interval of 70-80 km/h, and the average traveling speed of the small-sized vehicle sample is much larger than the traveling speed with the stream in each road segment. In terms of the medium-sized vehicles, the deviation between the traveling speed with the stream and the average traveling speed is small in road segment G0-G3, the deviation is larger in road segment G3-G6, and the traveling speed with the stream is less than the average speed. The average traveling speed of the large-sized vehicle is less than the traveling speed with the stream in segment G0-G1, and in the remaining segments, the average speed is higher. Comparing the absolute value of the deviation between the average speed and the traveling speed with the stream, it can be found that the average traveling speed values of the selected medium-sized and large-sized samples are larger than the corresponding traveling speed with the stream in each segment, but the deviation is smaller than the small-sized vehicle. Furthermore, the overall average traveling speed of the three samples is larger than the traveling speed with the stream in every segment. We can infer that the traffic volume on the entire path during this time period may be relatively smaller, resulting in a high average traveling speed, the results on the G5-G6 segment are the most prominent. However, in each road segment, the speed of the small-sized vehicle is similar to that of the medium-sized vehicle.

Figure 6(c) shows the traveling time with the stream of each road segment. The traveling time with the stream of the large-sized vehicle is longer than that of the other two types, the traveling time with the stream of the medium-sized and small-sized vehicles is quite close, and the deviation between these two is up to 12 s, while the minimum value is 2 s. This reflects that the traveling speed of these two types of vehicles might be similar in the real world.

Figure 6(d) shows the estimated traveling time on each road segment from the entry toll gate to the exit toll gate. We can infer that the estimated traveling time is positively correlated with the length of the road segment. Taking the small-sized vehicle sample as an example, the estimated time is 89 s on the shortest segment G4-G5, and the estimated time is 243 s on the longest road segment G2-G3. The results are consistent with the actual conditions without considering abnormal traffic conditions, such as congestion. Similar conclusions can be drawn from Table 3, 4, 5 and 6 in the appendix.

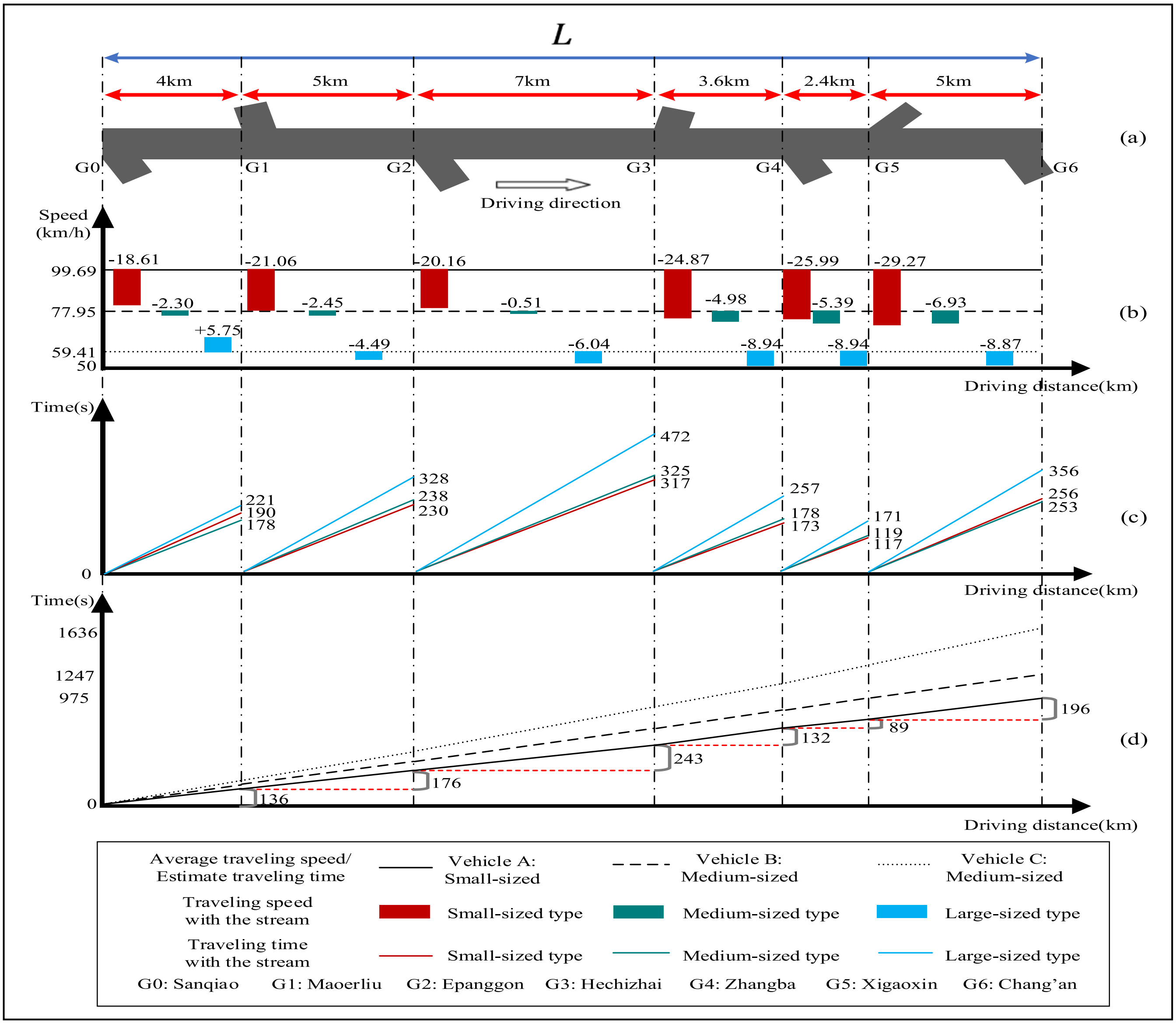

FIGURE 6. **Procedures for acquiring the estimated traveling time in each road segment. (a) Freeway structure from Sanqiao toll gate to Chang'an toll gate; (b) Average traveling speed of each vehicle on the path and traveling speed with the stream of each road segment; (c) Traveling time with the stream of each road segment; (d) Estimated traveling time in each road segment of each vehicle.**

The accuracy of VDs on the city ringway is not reliable because many of them are either broken or cannot collect complete traffic volume data. This paper verifies the accuracy of the derived historical traffic volume via TVDE. The selected TVDE is located on the road segment from the XigaoXin toll gate to the Chang'an toll gate, 2.085 km from the XigaoXin toll gate. The collection time of the verified data is from March 12 to March 18, 2018, including five weekdays and two weekend days. Figure 7 shows the results of the derived traffic volume and the corresponding traffic volume obtained from the TVDE in 15-minute interval. The MAE value of the derived data is 66.98 vehicles per 15 minutes. Both the derived data and TVDE data reflect a similar tendency. For example, more traffic volume is obtained on weekdays than on weekend days. There are two peak periods for each weekday, which are concentrated at 8:00 am and 6:00 pm, on weekend days, there are more vehicles at 6:00 pm, which is clearly shown on the derived data and TVDE data.

Compared to the deviation between the derived data and TVDE data, a higher volume is observed on the derived data than that of TVDE. This may be due to the inconsistency of the vehicle type classification during the deriving process, and the small-sized vehicles may include other vehicles of which average traveling speed is smaller than the small-sized vehicle, resulting in a smaller traveling speed with the stream of the small-sized vehicle on each road segment, and the corresponding traveling time with the stream becomes longer.

TABLE 1. **MRE value, MAE value and RMSE value of different structures of the SAE model.**

Hidden Layers	2 Layers		3 Layers		4 Layers	
Hidden Units	300,300	400,400	300,400,300	400,400,400	300,400,400,300	300,300,300,300
MAE	**29.484**	30.468	29.814	30.741	35.523	32.309
MRE	**0.131**	0.166	0.146	0.165	0.157	0.179
RMSE	**39.625**	42.518	39.768	43.057	53.543	45.965

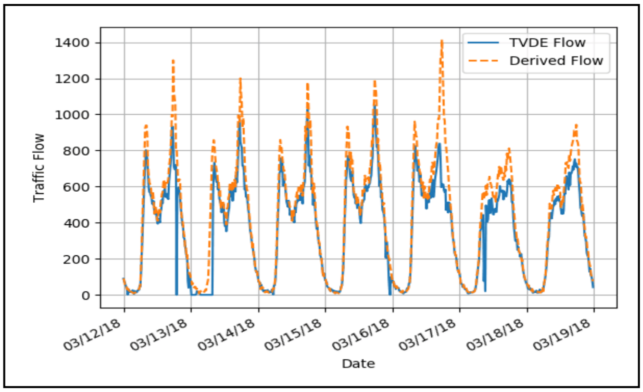

FIGURE 7. **Deriving the results of the traffic volume and that of the TVDE volume in one week (March 12-March 19).**

Because the ratio of the traveling time with the stream on each road segment to the sum of the traveling time with the stream on the entire traveling path decreases, the estimated traveling time in each road segment decreases, which means the derived time of the vehicle arriving at the target cross-section is ahead of the actual time. Therefore, when the vehicle has not reached the target cross-section, the vehicle has been included in the derived results. The length of the vehicle's traveling path obtained from the Dijkstra algorithm may be shorter than the real traveling path, and some vehicles may stay in the service area. These are also the reasons why the vehicle has been included in the derived results while it has not reached the target cross-section, which leads to an increase in the derived traffic volume. It can also be seen from Figure 7 that the trend of the derived data is roughly the same as the TVDE results. However, in the TVDE results, the traffic volume is 0 at most time from 0:00 am to 7:00 am on March 13th, and this might be a factor that causes a deviation between the derived traffic volume and the TVDE results. We infer that the malfunction of the TVDE might cause the result.

D. TUNING PARAMETERS OF THE SAE MODEL

When inputting the collected traffic volume data to the network, the SAE model can find the correlation between the traffic volume at different time intervals and may take advantage of the results to predict the traffic volume. However, if the structure of the model is different, the prediction accuracy will also change. To acquire the optimized prediction results, the influencing factors considered in this paper are listed as follows:

TABLE 2. **Performance comparison of the MAE for SAE, the DNN, the GRU, the RNN and the LSTM.**

Models	5-minute	15-minute	30-minute	60-minute
DNN	14.24	29.96	76.02	176.07
RNN	14.51	28.15	75.10	169.86
GRU	14.07	28.42	65.09	163.19
LSTM	14.58	28.80	68.16	161.51
SAE	14.65	29.48	65.63	165.67

- With the same structure, various training samples could lead to different results. Therefore, we aggregate the data into 5-minute intervals, 15-minute intervals, 30-minute intervals, and 60-minute intervals.
- The dropout value can be chosen by using a validation set, or it can be set to 0.5, which is optimal for many networks. After many experiments, we chose 0.2 as the dropout value.
- The number of hidden layers and the number of units in each layer are significant design factors. They determine the predictive performance of the models to some extent. For 15-minute interval traffic volume prediction, Table 1 shows the MRE values, the MAE values and the RMSE values of different structures of the SAE model. The exhibited value of each structure is the average value acquired after six experiments. A series of experiments demonstrate that 2 layers can be the best structure in a 15-minute interval, and the distribution of the units is [300, 300]. For the 5-minute interval, the 30-minute interval and the 60-minute interval traffic volume prediction, the distribution of the units are [300, 400, 300], [400,400,400], [400,400,400,400], respectively.

E. FORECAST TRAFFIC VOLUME AT THE DESIGNATED CROSS-SECTION

After comparing the forecast results of the SAE model with the estimated traffic volume of the designated cross-section in January 2018, the results indicate that the forecast results of the SAE model have similar fluctuation tendencies as the input data. The predicted results reflect that the proposed SAE model can perform well in forecasting the designated cross-section traffic volume in the real world.

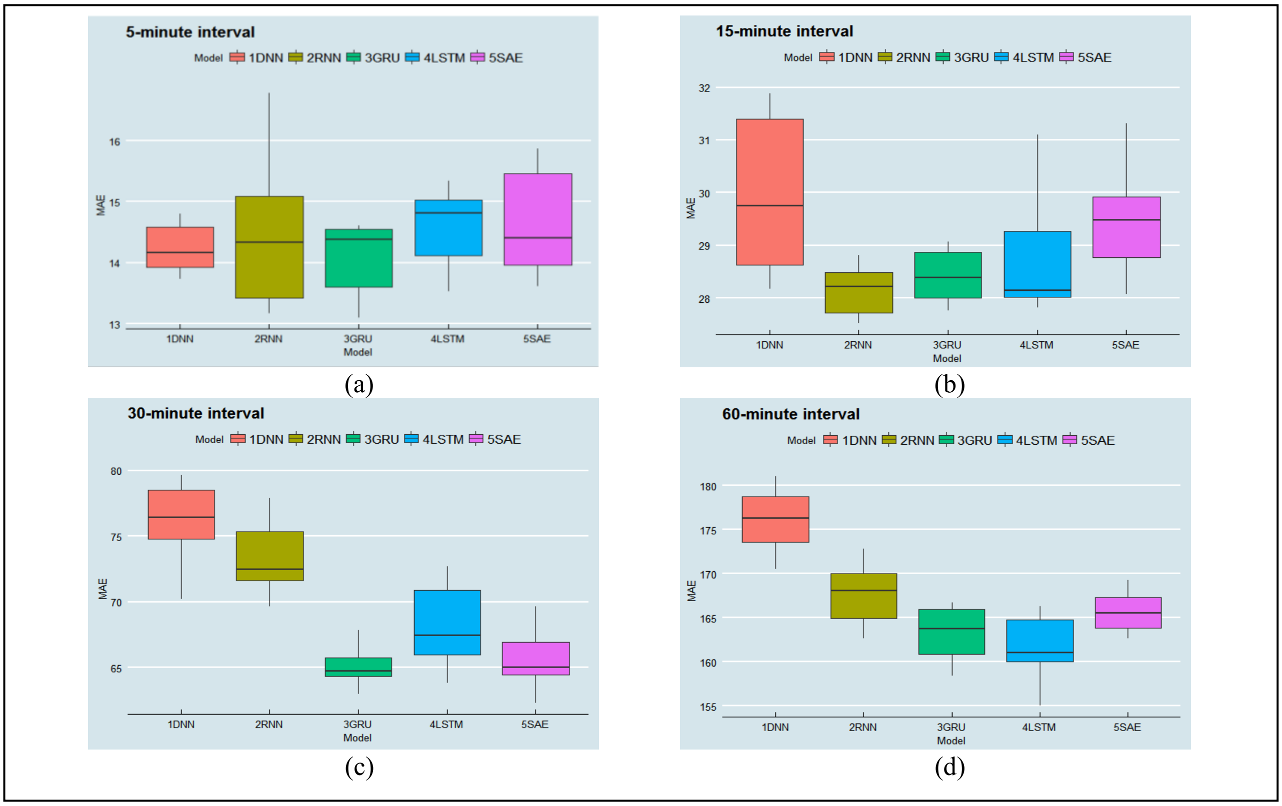

FIGURE 8. Performance comparison of SAE model with some existing methods for traffic volume predictions. (a) 5-minute interval; (b) 15-minute interval; (c) 30-minute interval; (d) 60-minute interval.

The performance of the proposed model is compared with other deep learning methods, including the LSTM, DNN, GRU, and RNN model. After a series of tests, we acquired a list of MAE values for each model to evaluate the performance based on the forecast results. As shown in Table 2, the proposed SAE network displayed better performance than some networks in 30-minute interval and 60-minute interval, but the forecast accuracy of SAE in 5-minute and 15-minute intervals is slightly worse than the other models. LSTM and GRU, as classic models widely used in forecasting time-series data, also show good performance in 30-minute and 60-minute intervals. In terms of the 5-minute and 15-minute intervals, the accuracy of RNN, DNN, GRU, SAE, and LSTM is quite close and RNN, GRU shows satisfactory performance, but as the forecast time increases, the accuracy of the RNN model decreases rapidly when compared with the SAE model, which has the same result that the RNN model is difficult to predict the traffic volume under long-term conditions because the vanishing gradient. Due to the continuous change of the traffic flow, the SAE model, by encoding and decoding procedures to reconstruct the input traffic flow data, can perform well in long-term traffic flow forecasts. Above all, the SAE model is practical compared with the other models.

To obtain a better understanding of the MAE values of the different approaches, the boxplots are used to show the MAE values of the different models in a visual approach, including the LSTM, DNN, GRU, and RNN models. Statistical results are added to present the different performances of each approach and display the discrete distribution of the MAE values. As shown in Figure 8, taking the 30-minute interval boxplot as an example, we can infer that the mean value of the MAE in the SAE model set is 65.63, one-quarter of the values are less than 64.5, and one-quarter of the values exceed 67. In other words, half of the value is between 64.5~67. Because the mean value of MAE is slightly higher than the median value, the MAE value in the SAE model is slightly larger. From the boxplots, we can draw the same conclusion from Table 2. Generally, the proposed SAE model is appropriate for the real-world situation to forecast arbitrarily designated cross-section traffic volume.

V. CONCLUSION

In this paper, we propose a systematic method to derive the traffic volume at arbitrary designated cross-section. Unlike the previous methods that only consider the limited data, the proposed method can successfully discover the latent attributes of the road segments on the freeways from large regional toll collection data and other traffic information including the traveling time/speed and so on. In addition, the nonlinear spatial and temporal correlations between the forecasted traffic volume and the massive toll collection data also explored via the basic attributes of road segments and other information, these findings could be contributions to the ITS.

TABLE 3. Average traveling speed (km/h) of each vehicle on the entire path.

Vehicle A	Vehicle B	Vehicle C
99.69	77.95	59.41

TABLE 4. Traveling speed with the stream (km/h) of each road segment.

Segment	Vehicle A	Vehicle B	Vehicle C
G0-G1	81.08	75.65	65.16
G1-G2	78.27	75.50	54.92
G2-G3	79.53	77.44	53.37
G3-G4	74.82	72.97	50.47
G4-G5	73.70	72.56	50.47
G5-G6	70.32	71.02	50.54

In the proposed traffic volume deriving model, first, the average traveling speed for an individual vehicle on the shortest path can be derived from the toll collection data. Then, we obtain the traveling speed with the stream and the traveling time with the stream of each road segment from the large sampling data with similar vehicle types, which is more appropriate in practice than its overall average traveling speed. The estimated traveling time cost in every road segment is obtained from this specified traveling speed and traveling time. The arrival time of each vehicle and the traffic volume at any designated cross-section can also be derived. In addition, we use the deep learning-based autoencoder to forecast the traffic volume and evaluate the prediction accuracy.

The experimental results show the effectiveness and satisfactory accuracy of predicting the traffic volume in the cross-section from a quick analysis of massive toll collection data. This may provide a practical method to derive traffic information without requiring the installation and regular maintenance of any additional equipment on the freeway and may prevent from unnecessary derivative congestion. The estimation and prediction of the traffic volume of a designated point have shown the effectiveness of the proposed method based on deducing from a toll collection data in a large-scale region. Although the data size is large, the computation speed is satisfactory with the similar high accuracy captured from measurement.

Although we have test the traffic volume deriving model and the prediction method, the accuracy of the estimation are affected by many other factors including weather changes, different types of cars, occasionally traffic congestions, etc. The improvement of prediction in the occasional situations is going to be further investigate in the future. More precisely estimation need to be further explored on the traveling speed, traveling time and traffic volume for individual vehicle. More situation and scenario could be used this proposed method to estimate the traffic flow from the toll collection data.

TABLE 5. Traveling time with the stream (s) of each road segment.

Segment	Vehicle A	Vehicle B	Vehicle C
G0-G1	178	190	221
G1-G2	230	238	328
G2-G3	317	325	472
G3-G4	173	178	257
G4-G5	117	119	171
G5-G6	256	253	356

TABLE 6. Estimate traveling time (s) in each road segment of each vehicle.

Segment	Vehicle A	Vehicle B	Vehicle C
G0-G1	136	174	229
G1-G2	176	225	296
G2-G3	243	311	408
G3-G4	132	169	222
G4-G5	89	114	150
G5-G6	251	329	196

APPENDIX

A list of results obtained in the procedure of estimating the traveling time is given in Table 3, 4, 5 and 6.

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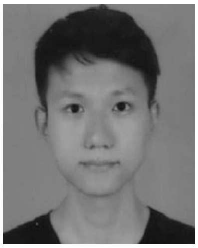

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