ISSN: 2472-3703 DOI: 10.6911/WSRJ.202005_6(5).0021

Research on Short-term Traffic Flow Forecasting Model Based on LSTM

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Abstract

Reliable short-term traffic flow prediction is one of the important components of intelligent transportation. In order to improve the prediction accuracy of short-term traffic flow and adaptability to different traffic conditions, this paper proposes a short-term traffic flow prediction model based on multi-dimensional influence factors. For the problem of traffic flow prediction in complex transportation systems, this paper uses the 5w model to classify the complex influencing factors in the transportation system, and uses the multi-dimensional related influencing factors of traffic flow together with historical traffic data as the input data of the model. The LSTM model is good at processing "sequence information" and learning long-term dependencies to perform high-precision short-term traffic flow prediction. Experimental results show that compared with the comparison algorithm, the multi-dimensional model has higher prediction accuracy and its average absolute error (MAE) is 11.37, the root mean square error (RMSE) is 13.99, the prediction accuracy rate is more than 90%, and it has good adaptability to different traffic flow states. The predicted value of traffic flow obtained by this model can reflect the trend of actual traffic flow well.

Keywords

Short-term traffic flow prediction; LSTM model; Multi-dimensional data.

1. INTRODUCTION

With the rapid development of the urban economy, highway transportation has gradually become an indispensable part of people's lives. Although in the development and construction of cities, the traffic control system is becoming more and more intelligent, and the road network structure is becoming more and more perfect, it is still unable to meet People's travel needs, traffic congestion is still an important factor restricting urban development[1].In order to alleviate urban congestion, cities around the world have gradually introduced smart transportation for effective traffic guidance and evacuation. Traditional traffic flow and congestion prediction models only rely on data such as historical traffic flow and speed of the road to make predictions, leading to excessive model dependence the original data, and the reliability of the original data will directly determine the accuracy of the model's prediction results. In the event of sudden conditions such as traffic accidents, heavy rain, etc., the prediction ability is severely reduced, resulting in the inability to accurately judge the traffic conditions of the corresponding road sections, and seriously Affect people's travel experience, and even make it difficult for the traffic management department to control road conditions in real time. And short-term traffic flow prediction is the most basic and important link in smart transportation. Improving the accuracy of short-term traffic flow prediction can effectively guide people's daily travel. For traffic management departments, traffic can be effectively channeled.

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The methods of short-term traffic flow prediction research at home and abroad can be roughly divided into three categories: (1) based on a single model: such as neural networks, deep learning, etc. Wang et al[2]Based on the theoretical framework of deep learning, a multi-time gradient traffic flow prediction model based on LSTM unit recurrent neural network is established; Liu et al[3]Select gated recurrent unit neural network(GRU) as the research object to make short-term prediction of traffic flow data; (2) Based on a combination model or model improvement, such as Kou[4] proposed an adaptive artificial fish swarm algorithm BP recurrent neural network (AAFSA-RNN) mode for short-term traffic flow prediction, which aims to improve the training speed of the neural network and the accuracy of model prediction; Tang et al.[5]in order to improve the prediction accuracy, a prediction method combining a denoising scheme and a support vector machine model was proposed; (3) Based on the data time series: Li et al.[6]Combining the periodic characteristics of traffic flow to reconstruct the time series, a traffic flow cycle prediction model is proposed; Yao et al. [7] took multiple sections of a road network as the research object, considered simultaneous prediction of multi-section flow, and established models and methods to predict traffic flow of road network from the perspective of road section. Li et al.[8]For the BP neural network, it has a good fitting effect on nonlinear relationships. The ARIMA model has a good linear fitting ability and separately models and predicts traffic flows. In terms of research on traffic influencing factors, Xiong[9]in the context of big data, he constructed a theoretical model of urban congestion based on the 5s element of traffic, which proved the effectiveness of adding traffic influencing factors to predict traffic congestion, and accurately and effectively evaluated urban traffic congestion; Lin[10]Multi-layer linear model was used to study the influence of rainfall intensity on the average driving speed of urban road traffic flow, and revealed the correlation between the factors affecting traffic flow. Gaode transportation[11]in the big data environment, the traffic data of Beijing and Shanghai in June were selected for the diagnosis of rainfall and weather congestion, and it was concluded that the traffic operation status of Shanghai was more sensitive to rainfall than Beijing.

From the above research status, we can know that although there are many traffic flow prediction models, the traffic flow data are mostly used as model inputs to predict traffic flow during modeling, and the influencing factors that cause non-linearity of traffic flow are ignored. However, The traveler's travel behavior is the direct cause of the change in traffic flow, and the behavior of the traveler at a certain time to select a specific path is affected by the specific situation[9]. This enlightens us to reconsider the prediction of traffic flow based on a large amount of traffic data and from the level of data mining[12].Therefore, in view of the shortcomings of the existing research, this paper analyzes the characteristics of traffic flow and the influence of space and time, and builds a 5W-based model of traffic influencing factors Multi-dimensional traffic flow prediction model for efficient and high-precision short-term traffic flow prediction.

2. 5W MODEL OF TRAFFIC INFLUENCING FACTORS

The transportation system is a combination of time and space. There are many factors that affect the change of traffic flow, including natural factors (such as terrain and weather conditions), economic factors (such as urban development status, per capita income level, vehicle ownership), and human factors (such as Residents' quality, travel mode), unexpected factors (such as traffic accidents, road construction), holidays, vehicle numbers, and other factors. Changes in the status of these factors will cause changes in traffic flow. Therefore, in order to better the above influencing factors Classification and integration. This article introduces a 5w model of traffic influencing factors.

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The 5W model was first proposed by the American scholar H. Lasswell in the paper "The Structure and Function of Communication in Society" in 1948, that is: what (event factor), where (place factor), when (time factor), who (Character elements), why (cause factors). These five elements decompose something in detail, and comprehensively describe the state of the event from different perspectives. This feature is in line with the impact of the state of the transportation system at each moment. The factor decomposition is interrelated with the factor decomposition of the traffic flow that we are going to carry out. It can be seen that it is feasible to combine the two and use the 5W model to establish a 5W model of traffic flow influencing factors. The relationship between the 5w-based traffic influence factor model and the traffic influence factors is shown in Table 1.

Table 1. 5w-based traffic influencing factor model

5w traffic influencing factor model	What	Traffic flow, traffic flow speed, traffic flow density, etc.
	where	Road width, number of upstream roads, number of bus stops, etc.
	When	Morning and evening peaks, working days, non-working days, holidays, etc.
	Who	Traffic managers, travelers, etc.
	why	Weather conditions, road construction, traffic accidents, etc.

3. LSTM ALGORITHM INTRODUCTION

With the development of machine learning, deep learning has gradually become the mainstream of traffic flow prediction. Deep learning methods can effectively use "sequence information" for traffic flow prediction without relying on prior knowledge. Long-term and short-term memory networks belong to recurrent neural networks (RNN). A recurrent neural network can use context-sensitive information in the mapping process between input and output sequences to make each data before and after the connection, rather than each individual, as shown in Figure 1. But Traditional RNN cannot capture long-term dependent information of the input sequence, and there are problems such as gradient disappearance or gradient explosion[13]Therefore, in order to solve the above problem, a long-short-term memory neural network LSTM is introduced. LSTM is a time-recursive neural network that is suitable for processing and predicting important events with relatively long intervals and delays in the time series, and can learn long-term dependencies, as shown in the figure As shown in Figure 2, proposed by Hochreiter and Schmidhuber (1997), and recently improved and promoted by Alex Graves[14]It improves the hidden layer of the ordinary RNN, replacing each hidden unit with a cell with memory function, and each cell adds 3 different gates to the previous state, the current input and the current The memories are called input gate, forget gate, and output gate, as shown in Figure 3, and then use different functions to calculate the state of the hidden layer. A piece of information enters the LSTM network and can be judged whether it is useful according to rules. Only information that meets the algorithm certification will be left, and non-conforming information will be forgotten through the forget gate. Practice has proven that LSTM is very effective for long-term dependence problems.

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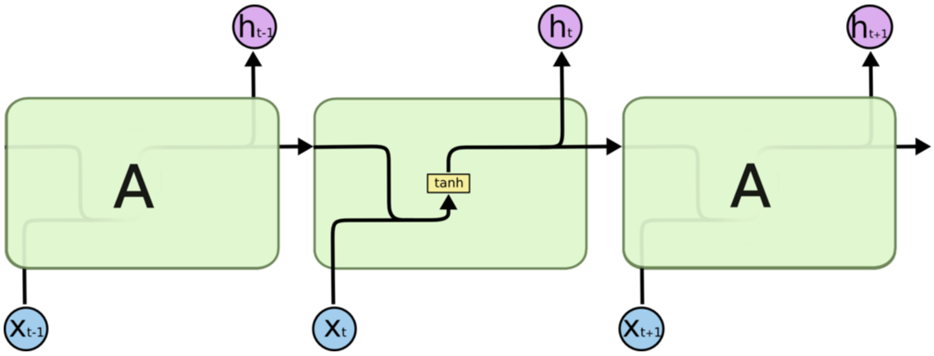

Figure 1. RNN model structure

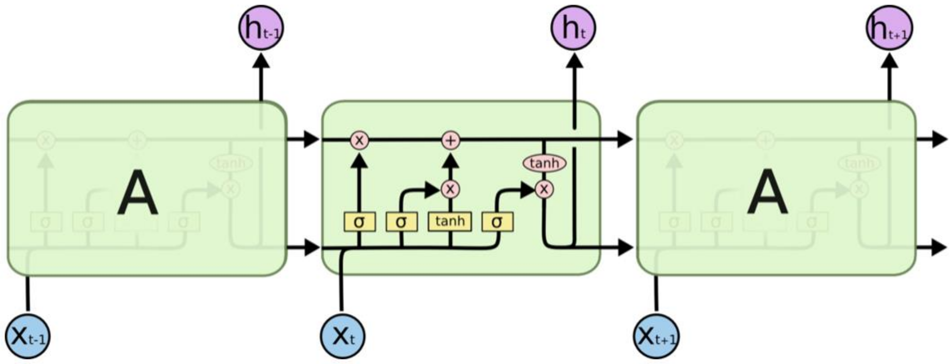

Figure 2. LSTM model structure

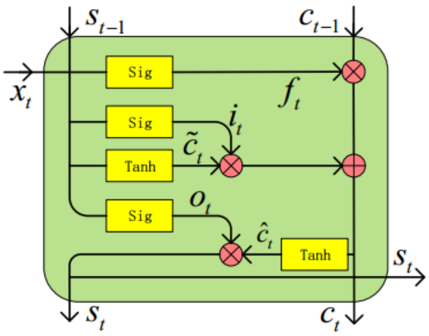

Figure 3. LSTM hidden layer structure

The calculation process of the LSTM single hidden layer memory cell at time t is as follows: x_t Represents the input data at time t, s_{t-1} Represents the hidden layer output at time t-1, c_{t-1} Unit status output at time t-1.

A. Calculate the output of the forgetting gate at time t f_t, Forgetting some past information, w_{Xf}, w_{sf} Forgotten Gate and x_t, s_{t-1} Weight, b_f Is the offset:

$$f_t = \sigma(w_{Xf}x_t + w_{sf}s_{t-1} + b_f) \tag{1}$$

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B. Calculate the output of the input gate at time t i_t To determine the input of the network at the current moment x_t How much is saved to the unit state c_t I.e. remembering certain information, w_{Xi} , w_{si} Represent input gates and x_t , s_{t-1} Weight, b_i Is the offset:

$$i_t = \sigma(w_{Xi}x_t + w_{si}s_{t-1} + b_i) \tag{2}$$

C. Based on the previous output s_{t-1} And this input x_t To calculate the memory of the current cell $c_t^{\sim}$,among them w_{Xc} , w_{cs} Represent unit status and x_t , s_{t-1} Weight, b_c Is the offset:

$$c_t^{\sim} = \tanh(w_{Xc}x_t + w_{cs}s_{t-1} + b_c) \tag{3}$$

D. Bring current memories $c_t^{\sim}$ And long-term memory c_{t-1} Combination to form a new unit state c_t Due to the control of the forget gate, it can save information from a long time ago, and due to the control of the input gate, it can also prevent the current insignificant content from entering the memory:

$$c_t = c_{t-1} \cdot f_t + i_t \cdot c_t^{\sim} \tag{4}$$

E. Calculation of output gate o_t ,among them w_{Xo} , w_{s0} Represent the output gate and x_t , s_{t-1} Weight, b_o Is the offset:

$$o_t = \sigma(w_{Xo}x_t + w_{s0}s_{t-1} + b_0) \tag{5}$$

F. Output of the memory cell at time t s_t :

$$s_t = o_t \cdot \tanh(c_t) \tag{6}$$

4. MULTI-DIMENSIONAL TRAFFIC FLOW PREDICTION MODEL

The traditional traffic flow prediction model only makes predictions based on historical traffic data, and with the development of the model, the prediction accuracy gradually improves, but the transportation system is affected by different factors at any time, which will reduce the model's adaptability and generalization ability, so Based on the 5w model, this paper proposes a multi-dimensional short-term traffic flow prediction model based on the lstm model. Based on the difficulty of data collection, this paper quantifies the working day, holidays, morning and evening peaks, and weather influencing factors into multiple data dimensions, together with the traffic flow Predict traffic flow as input data. The input of the model can be $x = (x_1, x_2, \cdots x_t)^T$, and the output of the model can be y_{t+1}. x_t is defined as the data of the current moment, which includes five data dimensions of road traffic flow to be predicted, morning and evening peak, working day, holiday and weather, that is $x_t = (z_1, z_2, \cdots z_5)$.

Specific steps are as follows:

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Step1: Sort the data of the five dimensions of traffic flow, weekdays, morning and evening peaks, weather, and holidays into suitable input formats and preprocess them, and map them to [0,1] using the minimum and maximum normalization;

Step2: Divide the data into two parts: training set and test set;

Step3: Determine the number of LSTM layers and the number of neurons in each layer;

Step4: Select the appropriate activation function and optimization algorithm;

Step5: Use the training set to train the model and output the error of each training to get the prediction model;

Step6: Use the test set to verify the prediction effect of the trained model;

Step7: Denormalize the data to get the predicted value.

Through the above 7 steps, the traffic flow prediction of LSTM neural network can be realized.

5. EMPIRICAL ANALYSIS

5.1. Data Sources

In order to test the prediction effect of the multi-dimensional traffic flow prediction model based on LSTM, this paper uses the traffic data published by the University of Minnesota Duluth to conduct an empirical analysis. The traffic data of the No. 509 detector at the intersection of 35e and 94, the weather information system The data of 330088 weather monitoring station in the study is used as the research object. The location of the flow monitoring point is shown in Figure 4.

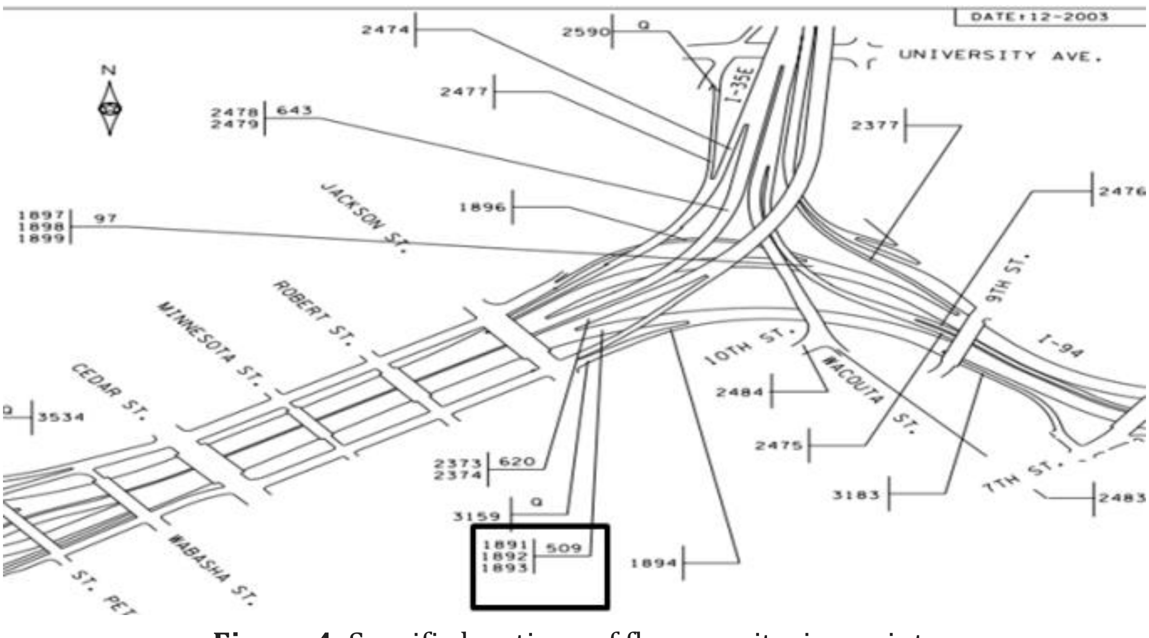

Figure 4. Specific locations of flow monitoring points

In this paper, traffic flow, working days, morning and evening peaks, weather conditions, and holidays on 28 solstice, May 1, 2018 were used as training data. Each data was separated by 15min, and the sample length of a day was 96. Some experimental data were shown in table 2. The data quantization mode is shown in Table 3. The traffic flow data on May 29 and 30, 2018 are used as test data to verify the prediction model. Data, such as data with low traffic flow, will be cleared from the data set, and for missing data, fill the data before the missing data to ensure the continuity and validity of the data set[15].

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Table 2. Some forecast data

time	509 traffic flow	Whether working day	Whether morning or evening peak	weather	Holiday
0:00:00	45	**1**	0	1	0
0:15:00	41	**1**	0	1	0
0:30:00	17	**1**	0	1	0
0:45:00	16	**1**	0	1	0
1:00:00	23	**1**	0	0	0
1:15:00	35	**1**	0	1	0
1:30:00	21	**1**	0	1	0

Table 3. Data quantification standards

type of data	Quantification standard
Whether working day	Monday to Friday is 1 and Saturday and Sunday are 0
Whether morning or evening peak	6: 00-8: 00 is morning peak, 16: 00-18: 00 is evening peak, morning and evening peak is 1, and non-peak is 0
weather	Sunny 0, Rain 1
Holiday	1 for holidays, 0 otherwise

5.2. Evaluation Index

In order to evaluate the accuracy of the prediction results, this article uses the mean absolute error (MAE) and the root mean square error (RMSE) as the evaluation indicators. The specific definitions are as follows:

$$MAE = \frac{1}{s}\sum_{i=1}^{s}\left|y_i^{\wedge} - y_i\right| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{s}\sum_{i=1}^{s}\left[y_i^{\wedge} - y_i\right]^2} \tag{8}$$

Where:y_iIs the actual value of the traffic flow,$y_i^{\wedge}$Is the predicted value of traffic flow, and s is the number of prediction samples.

5.3. Experimental Results and Analysis

According to the results of multiple experiments, this paper sets the multi-dimensional prediction model used to 4 layers, that is, the input layer, two hidden layers, and the output layer, and the number of hidden neurons is 100. In order to prevent overfitting, the Dropout layer is added and Set the random disconnection of 10% of the neurons. At the same time, the addition of the Dropout layer can also speed up the training of the LSTM model. The predicted trend diagram after prediction according to the above steps is shown in figure 5, it can be seen that the prediction of the multi-dimensional prediction model Although the values do not completely fit the actual values at the extreme high peaks, the predicted values and the true values are basically the same, and they can still better reflect the time-varying characteristics of the traffic flow, indicating that the prediction model proposed in this paper is It is feasible in actual traffic flow prediction.

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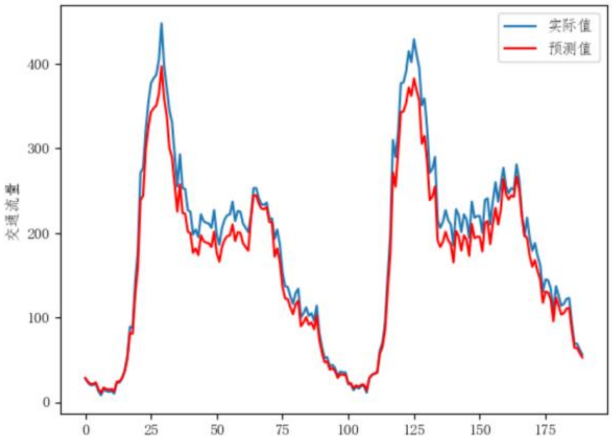

Figure 5. Forecasting trend of the multi-dimensional prediction model

In order to prove the effectiveness of different influencing factors on short-term traffic flow prediction, this paper compares the prediction results of multi-dimensional prediction models with different influencing factors, and the comparison results are shown in Table 4. From the comparison results in Table 4, we can see that different When influencing factors can have a certain effect on the prediction results, and the factor of working days has a significant effect on improving the accuracy of short-term traffic flow prediction. Combining data from multiple factors to predict the model's prediction results has a greater impact Significantly, the prediction accuracy is higher.

Table 4. Comparison of multi-dimensional prediction models with different influencing factors

Influencing factors	no	Working day only	Morning and evening peak only	Weather only	Four factors: weekdays, morning and evening peak weather, and holidays
RMSE	21.007	18.518	20.834	20.412	14.810
MAE	17.569	14.570	17.185	15.566	11.560

In order to evaluate the effectiveness of multi-dimensional prediction models in traffic flow prediction, this paper constructed two models: (1) LSTM model; (2) multi-dimensional prediction model, and compared the prediction effects of the two models. To test the accuracy of the prediction method It will predict the training samples of different lengths separately. Table 5 shows the comparison of the prediction errors of the two prediction models under the training samples of different lengths.

It can be seen from Table 5 that with the increase in the number of samples, the prediction error of the model is continuously reduced and the prediction accuracy is continuously improved. Compared with the LSTM model that only inputs traffic flow data, the prediction error of the multi-dimensional prediction model is better than the LSTM model. The prediction result is better than the comparison method on both evaluation indicators, indicating that the multi-dimensional prediction model proposed in this paper is an effective short-term traffic flow prediction model.

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Table 5. Comparison of model prediction errors

Error index	method of prediction	Number of training samples (days)		
		28	20	10
MAE	LSTM	17.246	18.809	22.26
	Multidimensional prediction model	11.37	13.98	20.73
RMSE	LSTM	20.123	22.411	25.187
	Multidimensional prediction model	13.993	17.509	23.838

6. CONCLUSION

Urban road traffic is a complex system that is affected by various dynamic factors and changes from time to time. Therefore, this paper considers the spatial and temporal characteristics of traffic flow and its influencing factors, constructs a 5w traffic influencing factor model, and proposes a multi-dimensional traffic flow based on LSTM. The prediction model validates the effectiveness of the model with actual data, and the results prove that the addition of traffic influencing factors has an impact on the accuracy of traffic flow prediction, and the multi-dimensional prediction model in this paper can predict short-term traffic flow with higher accuracy. Limitations of data collection, many influencing factors such as traffic accidents, road construction, etc. have not been reflected in this article, but the prediction results of the four influencing factors of weather, morning and evening peaks, working days, and holidays have shown that they have been added to the prediction model. It can effectively improve the accuracy of short-term traffic flow prediction, which has certain implications for the traffic management department to make higher-precision traffic flow prediction.

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