Traffic flow prediction model based on variational modal decomposition and Transformer

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ABSTRACT

In recent years, with the rapid development of national economy and transportation, the number of motor vehicles has increased dramatically, and the resulting traffic problems have aroused widespread concern. However, traffic flow is easily affected by weather, historical traffic flow and human factors, so traffic flow has the characteristics of randomness and nonlinearity, so using a single forecasting method to predict traffic flow can not meet the needs of modern intelligent transportation system. In order to improve the accuracy of traffic flow prediction, a traffic flow prediction model TF-VMD based on Variational Mode Decomposition (VMD) and Transformer is proposed in this paper. We use VMD method to decompose the traffic flow time series into k modes, and use Transformer model to predict the traffic flow in the next period of time. Finally, we superimpose the prediction results of each mode to obtain the final prediction results.Through experiments on real traffic flow data, compared with other prediction methods, the prediction results are improved in average absolute error, average absolute percentage error and equality coefficient, which effectively verifies the superiority of the model.

Keywords: Traffic flow forecast; Variational mode decomposition; Transformer model

1. INTRODUCTION

1.1 Research background and significance

Urban traffic flow is a complex nonlinear process. Traffic flow prediction is a necessary step to realize urban traffic adaptive control system and time optimization, and it is the guarantee for the smooth operation of traffic flow guidance system and ITS[1]. The prediction effect directly affects the efficiency of traffic control.The purpose of traffic forecasting is to predict the traffic conditions (such as traffic volume or speed) of future road network according to historical observation data (such as data recorded by sensors). Accurate traffic forecasting can help us to better control traffic and reduce the occurrence of congestion.The intelligent transportation system mentioned can achieve comprehensive and timely prediction of urban roads by using the Internet of Things model framework, big data technology, real-time information sharing and other functions, which can greatly improve the efficiency of road traffic, further improve infrastructure construction, speed up emergency response, etc., and become the key to building a "smart city"[2].

1.2 Limitations of traditional methods

Traditional traffic flow forecasting methods have some limitations, and it is difficult to cope with the complexity of urban traffic flow. For example, based on neural network prediction method, Cheng Shanying [3] used fuzzy neural network for prediction. Li Song et al. [4] combined with particle swarm optimization algorithm to improve and study the prediction model of BP neural network. For certain road data, neural network has better prediction results than other models. However, the neural network model belongs to the "black box" type, so it is impossible to know the specific form of the model, explain it with mathematical theory, and its specific application scope is difficult to be determined artificially. There are also some methods based on deep learning. For example, Yu Donghai [5] proposed a method of adding the influencing factors between traffic flows at intersections to the spatio-temporal matrix as input and using convolution neural network to predict. Wang Miaomiao [6] applied the long-term memory model to short-term traffic flow prediction for the first time. Although the deep learning method solves the problem of low prediction accuracy to a certain extent, its workload is too large and the calculation time is too long.

Some scholars use non-parametric method to forecast traffic flow, which has high accuracy.such as,Liu Mingyu et al. [7], Luo Wenhui et al. [8], based on the structure of neural network, use cross-validation method to verify the performance of nonparametric model in traffic flow prediction, and confirm the prediction accuracy of nonparametric model in this

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respect. However, due to the complex problems such as spatio-temporal correlation and nonlinearity of traffic flow data, the original traffic flow data will be disturbed to a certain extent during the collection process, which seriously reduces the prediction accuracy of this method.

In addition, the hybrid forecasting model has become the mainstream of current traffic flow forecasting. For example, Qiu Dunguo et al. [9], according to the time characteristics of traffic flow data, brought the data of N1 days and N2 days before the current time into ARIMA model for forecasting and determining the weight, and took the weighted average as the predicted value. The results show that this method has higher accuracy than a simple method. Li Dewei et al. [10] used the methods in the field of short-term traffic flow forecasting to forecast subway passenger flow, and used weighted historical average autoregressive model, ARIMA model and wavelet neural network model to combine forecasting and improve the forecasting accuracy. Zhu Yongqiang et al. [11] used a method based on CEEMD combined with LSSVM to study the model at different scales, which reduced the prediction error. Yang [12] adopts the model combination of multimodal and automatic encoder, and makes multi-step prediction for data. Shen Fuxin et al. [13] used CEEMD and GRU to construct a traffic flow prediction model, which was verified on the measured data of Shanghai Expressway and achieved certain results.Bing Qichun et al.[14]the multimodal method is used to forecast traffic flow, and its effectiveness is verified on data sets.Wang Xiangxue et al.[15]based on LSTM model, a traffic flow prediction model of urban expressway using cyclic neural network is constructed. The model has high prediction accuracy, and its practicability and expansibility are also improved to some extent.

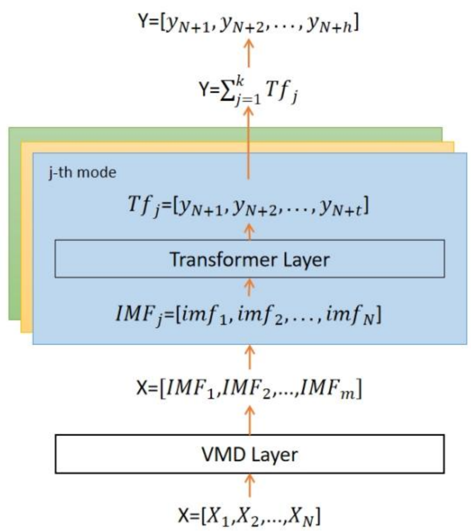

Figure 1. TF-VMD model diagram

All the above methods have been validated on real data sets, but the prediction accuracy of these models is not ideal because of the modal aliasing problems of EMD[16] and its improved algorithm. Based on these, in order to further improve the accuracy of traffic flow data prediction, the proposed traffic flow prediction model TF-VMD, VMD algorithm based on variational modal decomposition (VMD)[17] and Transformer[18] can effectively divide the traffic flow time series into multi-modal, to a certain extent, result in the problems of mode aliasing and endpoint effect, etc. The flow chart of the model is shown in Figure 1.By deeply mining the local characteristics of traffic flow time series, while Transformer can adaptively capture the long-range dependence in the time series and improve the generalization ability of the model in the task of time series prediction, which can effectively improve the prediction accuracy. In the following part, we will introduce the principle and experimental results of this innovative model in detail to prove its effectiveness and performance superiority in urban traffic flow prediction.

2. RELATED WORK

In this part, we will discuss the principles and advantages of the proposed traffic flow forecasting model based on variational mode decomposition (VMD) and Transformer, and the reasons why we choose to combine these two technologies.

2.1 Variational mode decomposition

VMD is a signal decomposition technology based on mathematical optimization. Its core idea is to decompose the signal into multiple modes, each mode represents the information of different frequency components and time domain characteristics in the signal. This decomposition process is adaptive, and there is no need to know the frequency or the number of modes of the signal in advance. The mathematical principle of VMD is based on variational method and constraints, and decomposition is realized by minimizing the coupling between modes. This enables VMD to effectively separate different frequency components, while preserving the temporal and spatial dependence of traffic flow. Its uniqueness lies in that it can decompose the signal into multiple modes (or components), and each mode represents the components with specific frequency and time domain characteristics in the signal.

2.2 Transformer model

Transformer model was put forward in 2017, and its uniqueness lies in completely abandoning the traditional structure of cyclic neural network (RNN) and convolution neural network (CNN), and replacing it with a brand-new architecture based on attention mechanism. The core idea of Transformer is to use self-attention mechanism to realize the modeling of sequence data, which enables the model to consider the information of each position in the input sequence at the same time, without relying on the previous hidden state like RNN. It shows strong modeling ability when dealing with serial data, so it also has a wide application prospect in traffic flow forecasting.

The architecture of Transformer model includes multiple attention heads and multiple self-attention layers. Each attention head can pay attention to the information at different positions in the sequence, thus realizing global modeling. This is very important for traffic flow prediction, because the temporal and spatial dependence of traffic flow may involve the correlation between different places and different times. By inputting the modal signals obtained by VMD decomposition into Transformer model one by one, we make full use of Transformer's advantages in spatio-temporal series modeling.

2.3 Combination of VMD and Transformer

The combination of VMD and Transformer is to overcome the limitations of traditional traffic flow forecasting methods. VMD provides multi-modal signals, which enables us to better understand the diversity and complexity of traffic flow. These modal signals can be regarded as the decomposition of different frequency components, and have good separation for traffic flow dynamics at different time scales. Transformer model can model the dependence between these modal signals in a global scope, capture the temporal and spatial correlation, and predict the future traffic flow more accurately.

The combination of VMD and Transformer provides a new method for traffic flow prediction. By making full use of multi-modal information and Transformer's powerful sequence modeling ability, the accuracy and robustness of prediction are improved. The specific implementation process of the model is shown in Figure 2.

- We divide the traffic flow data set into training set and test set according to the ratio of 4: 1. This partition ensures that we have enough data for model training and can verify the accuracy on independent test sets.
- on the training set, we use VMD technology to decompose the traffic flow data. In this study, we determine the appropriate number of decomposed modes according to the stability of the center frequency of the decomposed modes. The purpose of this step is to decompose the original traffic flow data into sub-signals with different frequencies, so as to better mine the time-frequency domain characteristics of the data.
- Next, we send the data of each mode to Transformer model for training. In Transformer, each mode is regarded as a sequence, and Transformer will learn the spatio-temporal relationship between each mode sequence. In this process, we can adjust the parameters of Transformer model, such as depth, number of heads, hidden layer dimension, etc., in order to better adapt to the complexity of traffic flow data.
- After getting the prediction results of each mode, we superimpose these results to get the final prediction results. This superposition method makes full use of the information of different frequency modes, and obtains a more comprehensive and comprehensive prediction. Then, we compare the prediction results with the independent verification set, and use various indicators (such as root mean square error, average absolute error, etc.) to evaluate the accuracy of the prediction.

We use two advanced technologies, VMD and Transformer, and have made remarkable progress in traffic flow forecasting. Firstly, we deeply study the application of VMD in traffic data processing, determine the appropriate decomposition modal number, and retain the important time-frequency characteristics of the data. Secondly, we tune the parameters of Transformer model in detail to ensure that it has strong expressive ability when learning spatio-temporal relations. Finally, we adopt the strategy of superimposing modal prediction results, which improves the comprehensiveness and accuracy of prediction. This method not only provides an innovative traffic flow prediction method, but also provides a new idea for further exploring the application of signal processing and deep learning technology in traffic data analysis.

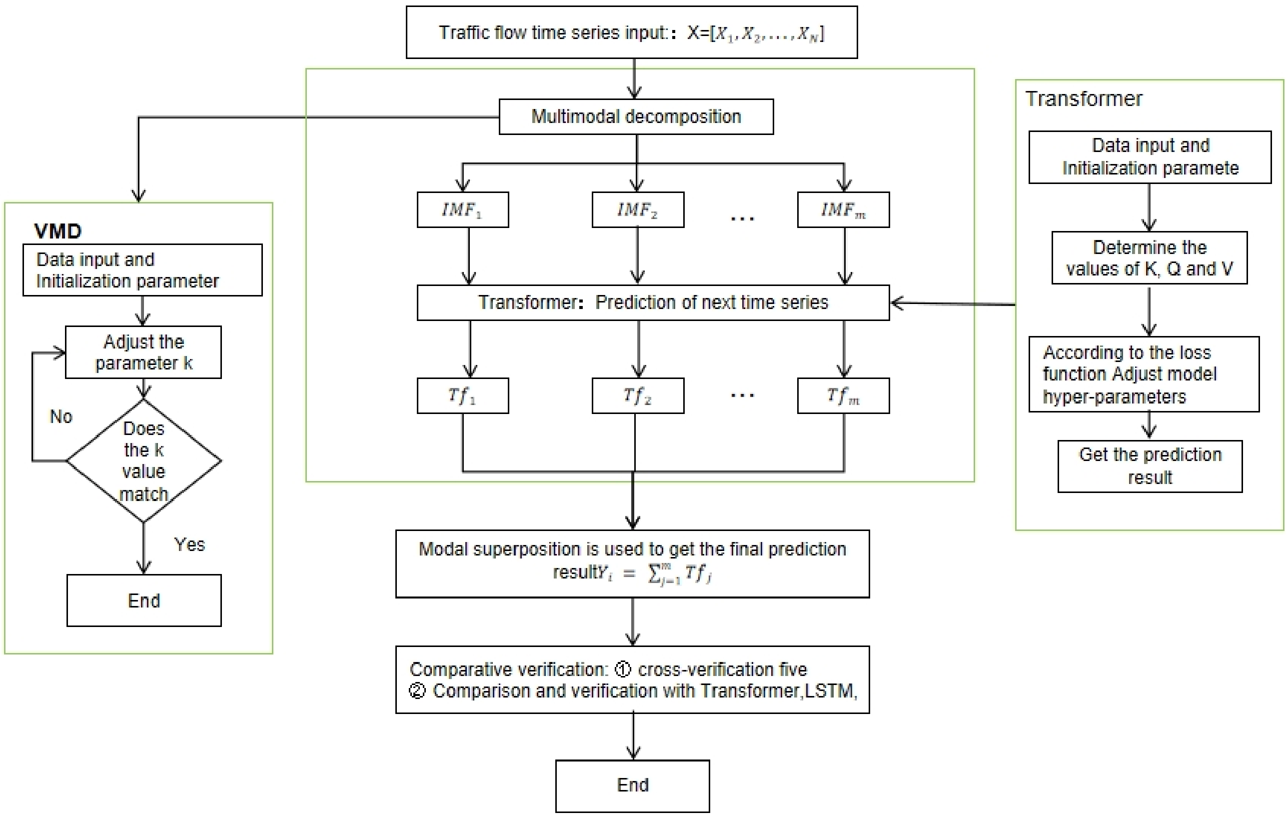

Figure 2. Model flow chart

3. EXPERIMENT

3.1 Introduction of data set

In the experiment, we used the historical traffic flow data from November 18, 2019 to November 23, 2019 on the south-north road of Wujia-Jucheng Road Station in Yichang City, Hubei Province, with the equipment number 42050300520001001203, including the traffic flow data of 16 intersections, and the time interval between samples was 5 minutes, with a total of 128,992 pieces of data to verify the effectiveness of the paper model. We select 80% of the data before each intersection in the data set for training, and the remaining 20% is used as the verification set to verify the predicted results.

3.2 Model flow chart

In this part, our main work is to decompose the original traffic flow time series into multiple modes, and mine their local characteristics under different time frequencies in order to achieve a higher prediction accuracy. As shown in Fig. 2, first of all, we should determine the value of parameter K according to the center frequency under multi-mode, and the value of K determines the number of decomposed modes. We set the parameters of VMD to alpha = 2000, tau = 0.5, tol = in the experiment, and then determine the value of k according to when the center frequency domain of its last layer tends to be relatively stable.

Finally, we set the k value to 6 and decompose the original traffic flow data into six IMF and one residual block. And different modal components show different local characteristics, and from IMF1 to IMF6, the center frequency domain distribution is uniform and separated clearly, effectively avoiding the mode stacking. In this way, we successfully decompose the original traffic flow data into multiple modes, and can better mine its local features in different time and frequency domains, which lays a foundation for the next prediction.

3.3 Result analysis

After training and evaluating the model, we analyze the experimental results in detail to evaluate the performance and effectiveness of the model.

After multi modal decomposition of traffic flow data, we send the first 80% of the data in each mode to Transformer for learning, and use the remaining 20% as verification set to verify the final prediction results. The Transformer super parameters are set as follows: the dimension of the hidden layer (d_model) is set to 64, the number of heads in the multi-head attention mechanism (nhead) is set to 4, the encoders (num_encoder_layers) and decoders (num_decoder_layers) are set to 2, and the iterations in the training process (epochs) are set to 50. Through the Transformer model to each modal data learning analysis, we will get each modal prediction resultsTf_{ij}.And the prediction results under each mode are superimposed as the final prediction results:$Y_i=\sum_{j=1}^{k} Tf_{ij}$.$Tf_{ij}$ represents the prediction result of intersection i under the j th mode,Y_i represents the final prediction result of the i-th intersection, and the modal number in this paper is 6.

In order to verify the accuracy of this method, we adopted a 50% cross-validation method. The experimental scheme is shown in the following figure. We divide the experimental data into five points on average, carry out five repeated experiments, send four parts into the model for learning and training each time, and use the remaining 20% as the accuracy of the data obtained after verification training. We carry out five repeated experiments respectively, The experimental steps are shown in Figure 3,and remove the average error of five times as the accuracy of evaluating the performance of the model.

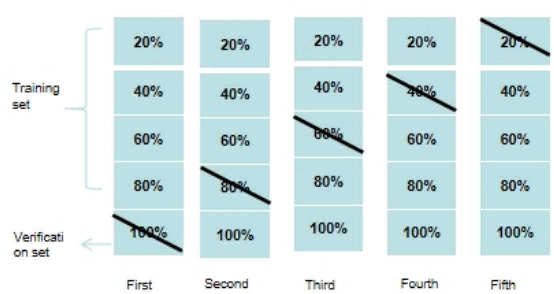

Figure 3. cross validation five method

For the prediction results obtained by cross-validation five, we select three indicators to analyze and evaluate: average absolute error (MAE), average absolute percentage error (MAPE) and equalization coefficient (EC). The average value of five verification results is taken as the evaluation index of the model.

TABLE 1. Prediction error of different models

Model	MAE	MAPE/%	EC
VMD-Transformer	6.32	6.98	0.988
VMD-Lstm	6.89	8.04	0.968
EMD-Transformer	7.89	9.72	0.944
Transformer	8.62	10.92	0.932
LSIM	9.06	11.89	0.928

It can be seen from the above table 1 that the prediction accuracy of the combined model is obviously higher than that of the single model, and it is feasible to further improve the prediction accuracy by using the method of modal decomposition before prediction. The analysis of experimental results will further support our argument and prove the applicability and performance superiority of the proposed traffic flow forecasting model based on VMD and Transformer in urban traffic flow forecasting tasks.

4. CONCLUSIONS

The experimental results show that the traffic flow prediction model based on VMD and Transformer performs well in the task of traffic flow prediction, and has achieved significant performance improvement. The main reasons for this promotion include the following:

- Modal decomposition: The traffic flow time series is decomposed into multiple modal signals, and each modal signal corresponds to different frequency components and time domain characteristics. This model fully considers the multi-modality of traffic flow, so that the model can better capture the traffic flow dynamics of different scales.
- Multi-model combination: The experimental results show that the scientific combination of models, compared with a single model, has a certain improvement in prediction accuracy.
- Advantages of VMD algorithm: Compared with EMD algorithm, VMD algorithm can effectively solve the problem of modal stacking, which can make the local time characteristics of each modal component more obvious and improve the prediction accuracy.

In addition, the experimental results show that our model has its advantages to some extent, but it also has some limitations:

- Our data set is sampled every five minutes. In the future work, we will use more distribution methods to process the data set, such as every 1 minute or 10 minutes to further optimize our model.
- This paper only considers the local characteristics of time and frequency domain in traffic flow data, while the real traffic flow data not only has time characteristics, but also has certain spatial characteristics. In the future work, we will consider the temporal and spatial characteristics of traffic flow data, for example, by analyzing the temporal and spatial correlation in traffic data, we will build a suitable model to further improve the accuracy of our model prediction.

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