International Journal of Scientific Advances
ISSN: 2708-7972
Volume: 5 | Issue: 1 | Jan – Feb 2024 Available Online: www.ijscia.com
DOI: 10.51542/ijscia.v5i1.15

Application of Autoformer to Short-Term Traffic Flow Prediction

Shuncai Luo* & Qingying Li

School of Transportation and Vehicle Engineering
Shandong University of Technology China

E-mail: 1693733232@qq.com; liqingyin@sdut.edu.cn

*Corresponding author details: Shuncai Luo; 1693733232@qq.com

ABSTRACT
This paper investigates the application of Autoformer model in the field of short-term traffic flow prediction. Traffic flow prediction is crucial for urban planning and traffic management, and is important for relieving traffic congestion and improving traffic efficiency. Autoformer, as a Transformer model based on the self-attention mechanism, provides a powerful modeling capability for the task of traffic flow prediction through its ability to automatically learn feature relationships. The paper first introduces the background and importance of traffic flow prediction and outlines current prediction methods and their limitations. Subsequently, the structure and working principle of Autoformer are described in detail, elucidating the advantages over traditional models. Autoformer's self-attention mechanism can effectively capture the long-range dependencies in the input sequences and better adapt to the dynamic changes of traffic flow. To verify the performance of Autoformer in short-time traffic flow prediction, experiments are conducted using real traffic flow datasets. The results show that Autoformer significantly improves the prediction accuracy and generalization ability compared to traditional time series models. In addition, model interpretive analysis was conducted, revealing the advantages of Autoformer for automatic extraction of traffic flow features and correlation modeling.

Keywords: autoformer; short-term traffic flow prediction; long-range dependencies

INTRODUCTION
With the continuous development of urban transportation systems and the acceleration of urbanization, traffic congestion has become one of the major challenges facing cities around the world. Traffic congestion not only affects the travel efficiency and quality of life of urban residents but also brings great pressure on the environment and economy. In this context, short-term traffic flow prediction has become an important part of the solution to urban traffic congestion.

Short-term traffic flow prediction aims to accurately predict the traffic flow within a short period of time in the future, and its accuracy is of great significance to traffic management, intelligent transportation systems, and travel planning. However, since traffic flow is affected by a combination of many influencing factors, such as traffic accidents, special events, holidays, etc., it is challenging to predict its changing trend. In past studies, traditional time series models and machine learning algorithms have been widely used in short-term traffic flow prediction, such as ARIMA [1], SARIMA [2], neural networks [3], etc., but there are some limitations in dealing with nonlinear, nonstationary and highly dynamic traffic flow data [4].

In recent years, with the development of deep learning technology, Autoformer, as an emerging model of attention mechanism shows better performance in dealing with time series prediction problems [5]. Autoformer combines the self-attention mechanism and the Transformer structure, has the ability to model sequence data, is suitable for capturing complex spatiotemporal relationships and nonlinear features, and thus has a broad application prospect in the field of short-term traffic flow prediction.

The purpose of this thesis is to propose an effective short-term traffic flow prediction method based on the Autoformer model, combined with the spatiotemporal characteristics of traffic flow data. By comparing the performance of the traditional model and the Autoformer model, the advantages and limitations in traffic flow prediction are explored, with a view to providing new ideas and methods for urban traffic management and the optimization of intelligent transportation systems.

GROUNDED THEORY
Transfomer Theory
Autoformer is based on Transformer, a deep learning model structure that was originally proposed for natural language processing tasks such as machine translation. Its main feature is the introduction of the self-attention mechanism, which allows it to handle long-range dependencies efficiently.

Later, the success of Transformer has been widely used in different fields, including image processing, audio processing, and temporal data processing [6], where temporal data processing is mainly reflected in time series prediction tasks [7]. The Transformer model consists of a position encoder, encoder, and decoder, and its structure is shown in Figure 1 below.

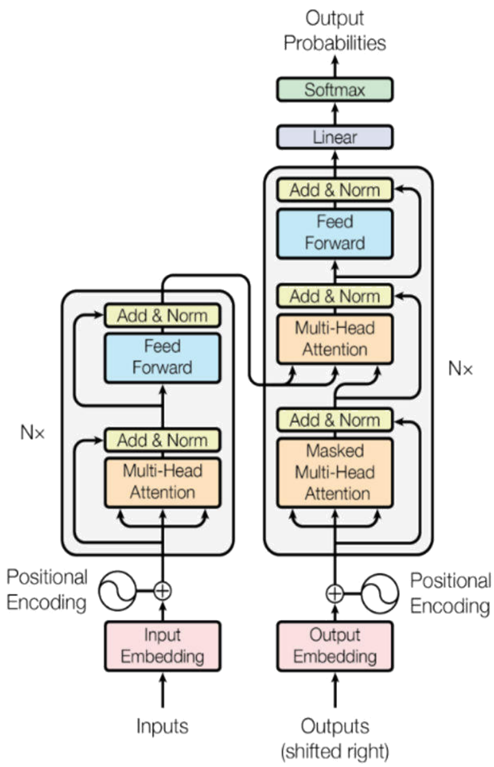

FIGURE 1: Transformer model structure.

The input layer feeds time series data into the Transformer model in a certain sequence of time steps. Typically, each time step in the sequence serves as a position in the model, and the feature vector at each position contains the observed timing information. Position encoding: In order to take into account, the order of the elements in the sequence, a position encoding needs to be added. This can be a fixed mathematical function, such as a combination of sine and cosine functions, or it can be learned. Output Layer: For the task of time series prediction, it is common to use a fully connected layer or other appropriate layer at the output of the model to generate the final prediction. Using the Transformer's encoder structure, the input sequence is processed through multiple self-attentive and feedforward neural network layers. The output can be a prediction for the last position or for all positions. The model is trained using an appropriate loss function (e.g., mean square error) to tune the hyperparameters, such as the learning rate, the number of attention heads, etc.

Autofomer theory

Autoformer model is improved on the basis of the Transformer model, which takes sequence decomposition as the traditional method of preprocessing, and proposes a deep decomposition architecture, which is able to decompose more predictable components from complex temporal patterns. Auto-correlation is proposed to replace the attention mechanism of pointwise connection to achieve sequence-wise connection and O(LlogL) complexity, breaking the bottleneck of information utilization. Its model architecture is shown in Figure 2.

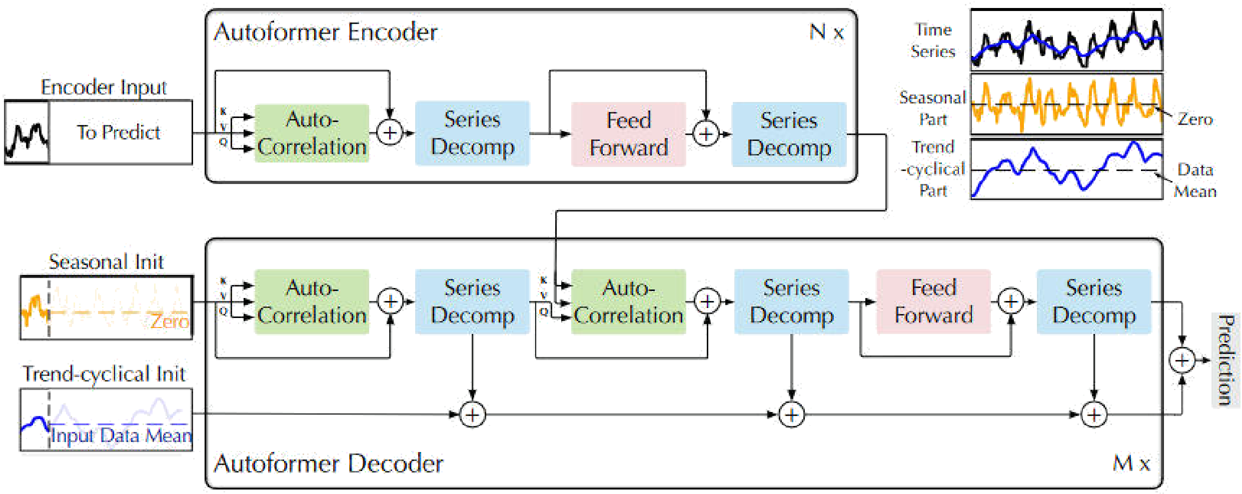

FIGURE 2: The model architecture of Autoformer.

In the prediction process, the trend term and cycle term are gradually separated from the hidden variables to achieve progressive decomposition, so as to realize the alternation and mutual promotion of decomposition and optimization of prediction results. Therefore, this paper applies Autoformer to short-time traffic flow prediction, validates it on real datasets, and uses LSTM and Transformer as the baseline model to compare and prove the effectiveness of Autoformer in short-time traffic flow prediction.

EXPERIMENTAL RESULTS

The experiments are carried out on real road network datasets, in order to verify that the model has a certain degree of generalization, this paper chooses a widely used dataset for short-term traffic flow prediction, respectively, using the data of the dataset PeMSD7 in the study to carry out traffic flow prediction experiments. After several debugging, the optimal parameter composition of Autoformer is obtained. Comparison is then done on the PeMSD7 dataset with two baseline models, LSTM and Transformer.

The experiments use the mean squared error (RMSE) and mean absolute error (MAE) to evaluate the model performance, which are expressed in Eq. (1) and Eq. (2).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i}^{n}(X_i - \tilde{X}_i)^2} \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i}^{n}|X_i - \tilde{X}_i| \tag{2}$$

$\boldsymbol{X_i}$ and $\boldsymbol{\tilde{X}_i}$ in Eqs. (1) and (2) denote the true and predicted values, respectively, and $\boldsymbol{n}$ denotes the number of data in the test dataset, whose prediction results are shown in Table 1.

TABLE 1: Projected results.

	RMSE	*MAE*
LSTM	7.65	5.32
Transformer	6.62	4.62
Autoformer	5.34	3.86

As shown in Table 1, the RMSE and MAE of Autoformer in this experiment are 5.34 and 3.86 respectively, and its results are better than those of LSTM and Transformer. Meanwhile, in order to visualize the prediction results.

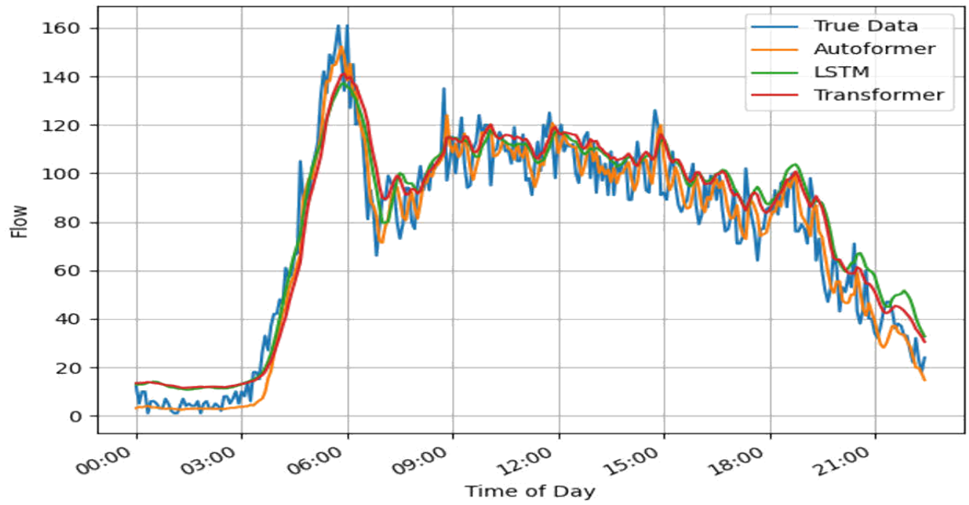

FIGURE 3: Experimental results.

As shown in Figure 3, Autoformer's prediction results are closer to the true values than those of LSTM and Transformer, thus proving its superiority.

CONCLUSIONS

In this paper, the structure and working principle of Autoformer are described in detail, and the advantages over traditional models are elucidated. The self-attention mechanism of Autoformer can effectively capture the long-range dependencies in the input sequences, and better adapt to the dynamic changes of traffic flow. To verify the performance of Autoformer in short-term traffic flow prediction, experiments are conducted using real traffic flow datasets. The results show that compared with the current LSTM and Transformer models used for short-duration traffic flow prediction, Autoformer significantly improves the prediction accuracy and generalization ability. In addition, model interpretive analysis was performed, revealing the advantages of Autoformer for automatic extraction of traffic flow features and correlation modeling.

ACKNOWLEDGMENT

Thanks to the Intelligent Transportation Association of Shandong University of Science and Technology for their help with this article.

REFERENCES

[1] Zhou, B., He, D., Sun, Z., & Ng, W. H. (2005, July). Network traffic modeling and prediction with ARIMA/GARCH. In Proc. of HET-NETs Conference (pp. 1-10).

[2] Nai, W., Liu, L., Wang, S., & Dong, D. (2017). An EMD–SARIMA-based modeling approach for air traffic forecasting. Algorithms, 10(4), 139.

[3] Pan, X., Zhou, W., Lu, Y., & Sun, N. (2019). Prediction of network traffic of smart cities based on DE-BP neural network. IEEE Access, 7, 55807-55816.

[4] Cai, L., Janowicz, K., Mai, G., Yan, B., & Zhu, R. (2020). Traffic transformer: Capturing the continuity and periodicity of time series for traffic forecasting. Transactions in GIS, 24(3), 736-755.

[5] Wu, H., Xu, J., Wang, J., & Long, M. (2021). Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting. Advances in Neural Information Processing Systems, 34, 22419-22430.

[6] Han, K., Xiao, A., Wu, E., Guo, J., Xu, C., & Wang, Y. (2021). Transformer in transformer. Advances in Neural Information Processing Systems, 34, 15908-15919.

[7] Kim, D. K., & Kim, K. (2022). A Convolutional Transformer Model for Multivariate Time Series Prediction. IEEE Access, 10, 101319-101329.