Wavelet Neural Networks: A Novel Approach for Precise Short-Term Traffic Flow Prediction

Xiaobo Yang

Abstract—**To improve the accuracy of short-term traffic flow predictions, this study advocates an approach utilizing wavelet neural networks. The research methodology is structured as follows: First, we analyze the reconstruction algorithm and foundational theory of wavelet transform. Next, we present a traffic flow prediction model that employs wavelet decomposition through a wavelet neural network, along with an examination of the learning process inherent to Kohonen's self-organizing neural network. Finally, we apply the proposed wavelet neural network prediction model to forecast traffic flow and compare its performance against traditional algorithms introduced in this paper. The results indicate that our method achieves a forecasting accuracy exceeding 90% when comparing predicted values from the wavelet neural network with actual traffic flow measurements at five-, ten-, and fifteen-minute intervals. This enhanced performance relative to other predictive methodologies—such as Deep SORT prediction method, YOLOV5 prediction method, and Convolutional Neural Networks method—across similar temporal scales reinforces confidence in the efficacy of our proposed strategy for accurate traffic flow estimation.**

Index Terms—**Wavelet neural network, Traffic flow forecast, Multiple time scales, Comparative analysis**

I. Introduction

THE analysis and prediction of short-term traffic flow is the fundamental component of an intelligent transportation system, forming the basis for traffic control and information services. Therefore, current research on intelligent transportation systems aims to objectively and efficiently assess and estimate short-term traffic flow using traffic flow data. Dai et al. [1] examined the prediction effect of the Kalman filter model, a linear system theory-based prediction technique with limited forecast accuracy, using traffic flow simulation data. Messai et al. [2] utilized reverse neural networks and real-time recurrent learning neural networks to anticipate and track traffic flow while studying neural network training and structure determination. These approaches demonstrate superior predictive efficacy compared to the linear regression prediction method. Yang et al. [3] proposed a support vector machine-based short-term traffic flow prediction model that outperforms the BP neural network in terms of accuracy and convergence. Yang et al. [4] employed wavelet analysis to examine traffic flow across the various temporal scales, resulting in an ARMA prediction model with an estimation accuracy of over 85%. Xue et al. [5] applied chaos theory for short-term traffic flow prediction, however, their model's limitations were evident in its inability to perform multi-step prediction, which necessitated the use of complex data phase space reconstruction. Stephen et al. [6] employed a multivariate non-parametric regression model to anticipate traffic conditions, which they validated using actual traffic data from London. Wu et al. [7] developed and validated a short-term traffic flow prediction technique, utilizing real-time traffic data and employing a BP neural network and the L-M algorithm.

In conclusion, while the linear system theory-based prediction technique is user-friendly and computationally complex, it needs more accuracy for predicting complex traffic scenarios. The intelligent algorithm successfully addresses many problems, exhibiting high robustness and yielding favorable application outcomes. However, it shows slow convergence in complex nonlinear scenarios. Although the accuracy rate of nonlinear system prediction approaches is commendable, their theoretical foundation needs more clarity and imposes significant computational demands. Single-step prediction is widely employed to create short-term traffic flow prediction algorithms.

In contrast, the exploration of continuous multi-step prediction still needs to be conducted, and the synthesis and prediction of diverse traffic data across various time scales are seldom considered. This research presents a novel approach using a wavelet neural network, a unique combination of wavelet transform and neural networks. This integration leverages their respective advantages to achieve accurate traffic flow forecasts and precise short-term traffic flow projections.

II. The Reconstruction Algorithm for the Wavelet Transform

By applying the wavelet transform to both the time and frequency domains of a signal, one can convert it into a continuous time-frequency domain representation. The wavelet function underlying this transformation acts as an expression of the wavelet transform.

$$C_{\varphi} = \int_{-\infty}^{+\infty} \frac{|\varphi(x)|^2}{|x|} dx < \infty \quad (1)$$

The formula (1) contains the wavelet generating function $\varphi(x)$ and the admissibility criterion $C\varphi$.

The expression for the continuous wavelet transforms of any signal $f(x)$ and any real pair (a, b) is provided below.

$$W_f(a, b) = \int_{-\infty}^{+\infty} f(x)\overline{\varphi}_{(a,b)}(x)dx \quad (2)$$

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A continuous wavelet transform is observed in formula (2). Given the discrete nature of the traffic data distribution, it becomes crucial to discretize this constant wavelet transform. By sampling the stretching factors '*a*' and '*b*' from the continuous wavelet transform, we can express the discretized wavelet transform as follows.

$$W_f(j,k) = \sqrt{2^j}\int_{-\infty}^{+\infty} f(x)\overline{\varphi}(2^j x - k)dx, \quad j,k \in Z \tag{3}$$

After undergoing discrete wavelet transformation, the high-frequency and low-frequency signals that have been decomposed will experience some degree of signal degradation, which can impact the conclusion drawn from predictions. Therefore, the Mallat reconstruction technique may recreate these decomposed signals [8]. The algorithm for this reconstruction is described below.

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$$C_j = H * C_{j-1} + G * D_{j-1}, \quad j = 1 \cdots N \tag{4}$$

The formula (4) represents the following: H denotes a low-pass filter, *G* represents a high-pass filter, C_j signifies the low-frequency information of the original signal, D_j indicates its high-frequency information, j stands for the number of decomposition levels, and *N* refers to the maximum number of decomposition layers.

III. Model for forecasting traffic flow based on wavelet neural networks

The original signal is subjected to wavelet decomposition, resulting in discrete frequencies. The reconstruction process integrates several sub-sequences of a single frequency on the original scale. Additionally, wavelet decomposition is utilized to smooth the original signal and produce a continuous function with enhanced continuity. Based on the characteristics of the input sample, a self-organizing neural network [9] performs self-organizing mapping. Accurate estimation of expected traffic flow values can be quickly achieved through automatic categorization and prediction using only limited training data samples. Figure 1 illustrates the wavelet neural network-based model for traffic flow prediction.

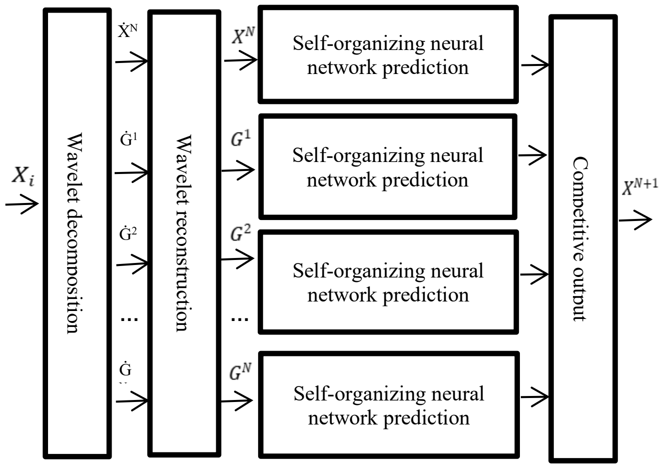


Fig. 1. Traffic flow prediction model based on wavelet neural network

The original traffic flow time series X_i undergoes wavelet decomposition, resulting in low-frequency $\dot{X}^N$ and high-frequency signals $\dot{G}^N$, as illustrated in Figure 1. Subsequently, wavelet reconstruction is performed to obtain decomposed and reconstructed time series signals X^N and G^N. The self-organizing neural network is the most suitable approach for prediction purposes, with the winning neurons providing accurate prediction results.

The conversion procedure between the deconstructed and reconstructed time series signal and the original traffic flow signal can be expressed as follows.

$$X_i = X^N + G^1 + G^2 + \cdots + G^N \tag{5}$$

The reconstruction outcome of the low-frequency signal at layer *N* is denoted as X^N, while G^1, G^2, and G^N represent the reconstructed high-frequency signals at layers 1, 2, and *N*, respectively.

This paper employs the Kohonen self-organizing neural network for competitive learning, with the specific learning process illustrated in Figure 2.

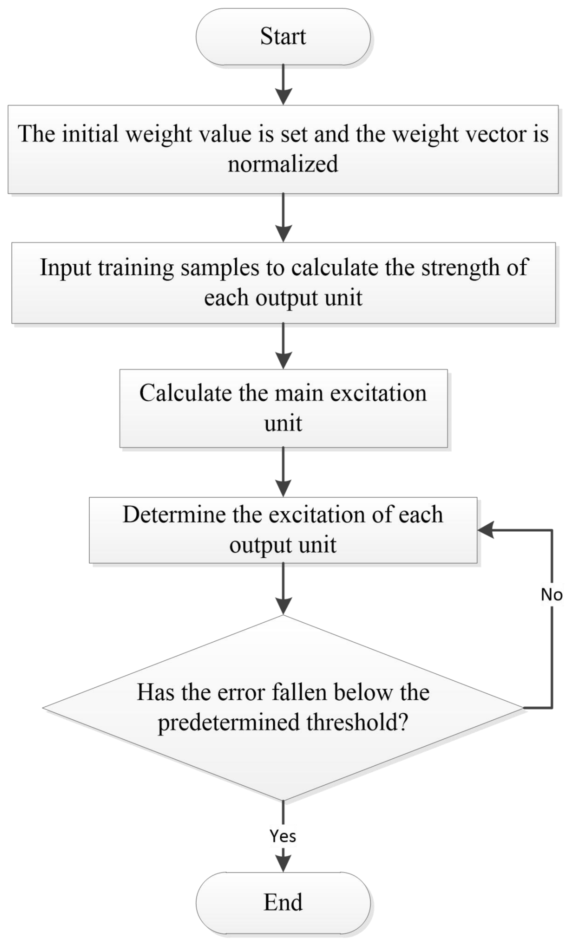


Fig. 2. Kohonen self-organizing neural network learning flow chart

The weight vector is normalized before calculation, as depicted in Figure 2, while the initial power is randomly selected. Subsequently, the primary excitation unit is determined by evaluating the strengths of each output unit using training samples as input. Conversely, the frequency of updating the learning rate depends on the number of learning opportunities, and each weight adjustment continues until the error falls below a predetermined threshold.

IV. Using a Prediction Model in Practice

The traffic flow on the Hangzhou North-South Viaduct was monitored to validate the forecast effect of the wavelet neural network prediction model. Data was collected using magnetic induction coils strategically installed along an approximately 8-kilometer-long selected segment, gathering data on traffic movement every 5, 10, and 15 minutes from 6 am until 11:30 pm over five labor-intensive days. A substantial amount of traffic data (7,790 pieces) was collected daily and categorized into two groups. The model underwent training with data recorded between October 17 and 29, 2022, was used for model training, followed by testing with data from November 2 to 18, 2022. The model was then employed to predict traffic patterns on November 25, 2022.

The wavelet decomposition approach demonstrates the following characteristics: improved forecast accuracy is achieved through finer signal division, increased stability of decomposed signals, and enhanced forecast precision. It should be noted, however, that the actual process error can impact forecast accuracy, with this error increasing as the number of wavelet decomposition layers increases. Extensive trials consistently show that prediction accuracy peaks when there are two decomposition levels. Therefore, for this investigation on wavelet decomposition layers, N is set to 2.

Figure 3 depicts the prediction process for a wavelet neural network, which is utilized in forecasting traffic flow data.

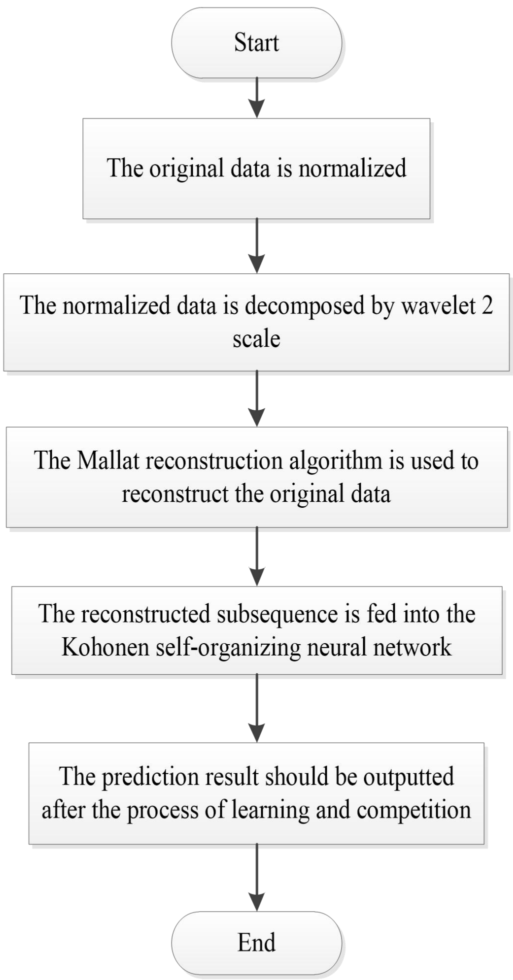
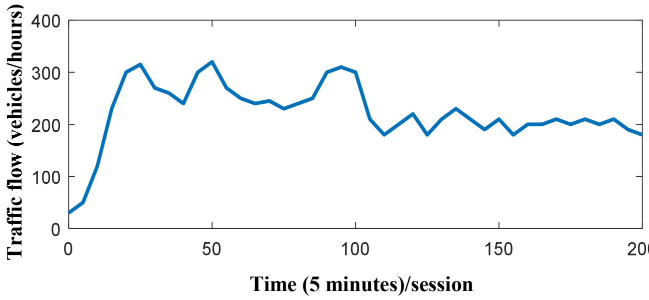


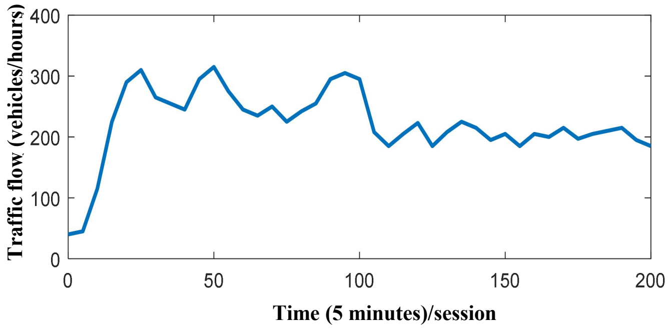
Fig. 3. Traffic flow information prediction process based on the wavelet neural network

Figure 3 demonstrates the necessity of initial normalization for the original traffic data, as it enables the wavelet scale two decompositions and facilitates the application of a wavelet neural network to predict traffic flow information. Afterward, the Mallat reconstruction technique should be used to restore the original traffic data, which can then be input into the Kohonen self-organizing neural network for learning and competition. The result of this prediction process is derived from the output value produced by successful neurons.

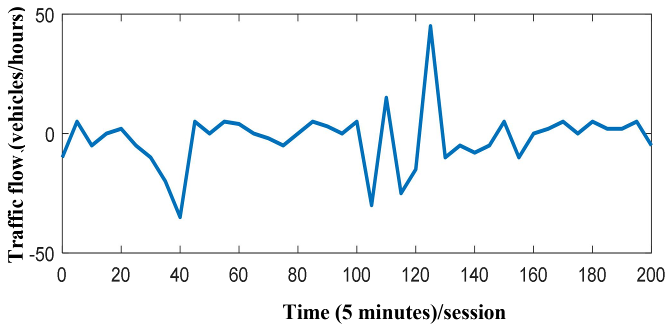
The results of the traffic flow reconstruction every five minutes and wavelet decomposition are presented in Figure 4.



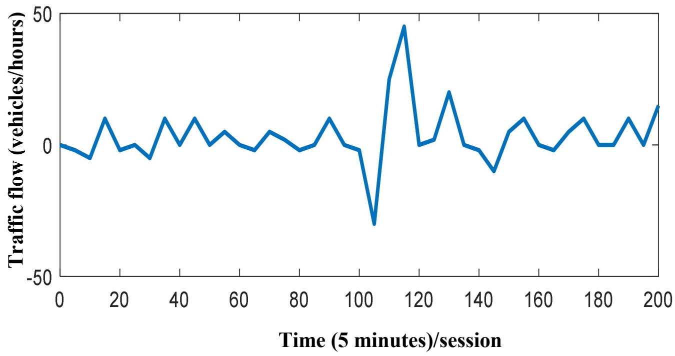
4(a) Original traffic flow



4(b) Layer 2 low-frequency reconstructed signal



4(c) Layer 2 high-frequency reconstructed signal

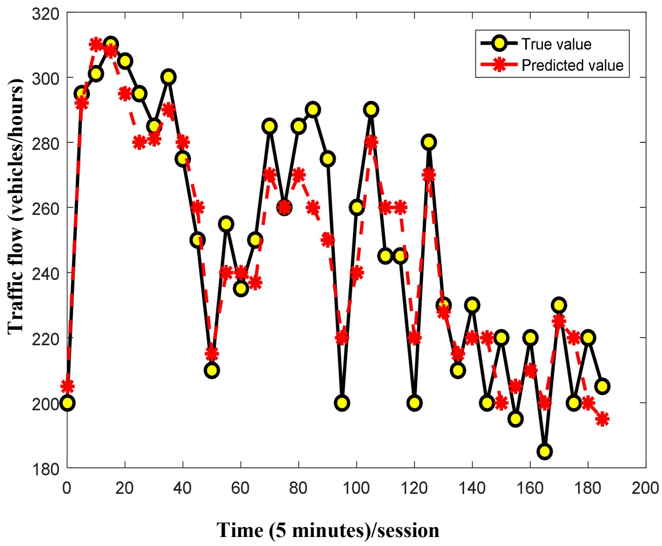


4(d) Layer 1 high-frequency reconstructed signal

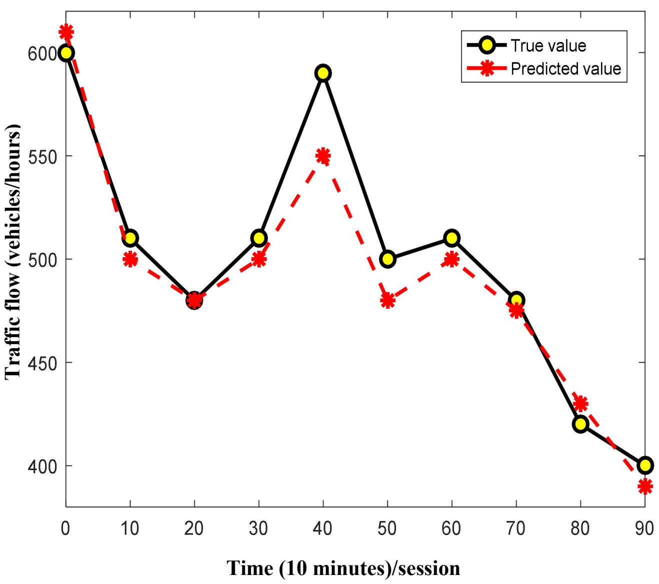
Fig. 4. Results of wavelet decomposition and reconstruction of traffic flow every 5 minutes

System noise can significantly disrupt the high-frequency component of the system output, leading to substantial fluctuations in the reconstructed signal, as illustrated in Figures 4(c) and 4(d). In contrast, utilizing a low-frequency reconstructed signal for the system output enhances stability. It reduces susceptibility to interference from system noise, as depicted in Figure 4(b), thereby making it more suitable for representing dynamic traffic flow patterns.

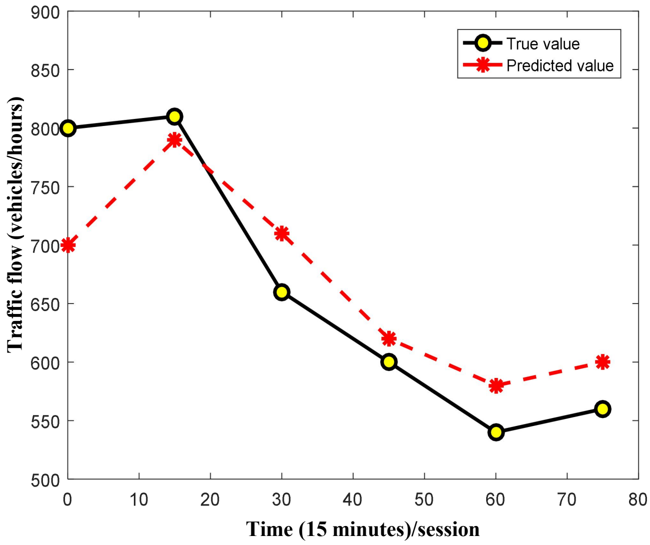
The accuracy of the wavelet neural network's prediction is demonstrated by comparing the expected and actual traffic flow numbers at five-, ten-, and fifteen-minute intervals, as shown in Figure 5.



5(a) Comparison of actual and predicted traffic flow (every 5 minutes)



5(b) Comparison of actual and predicted traffic flow (every 10 minutes)



5(c) Comparison of actual and predicted traffic flow (every 15 minutes)

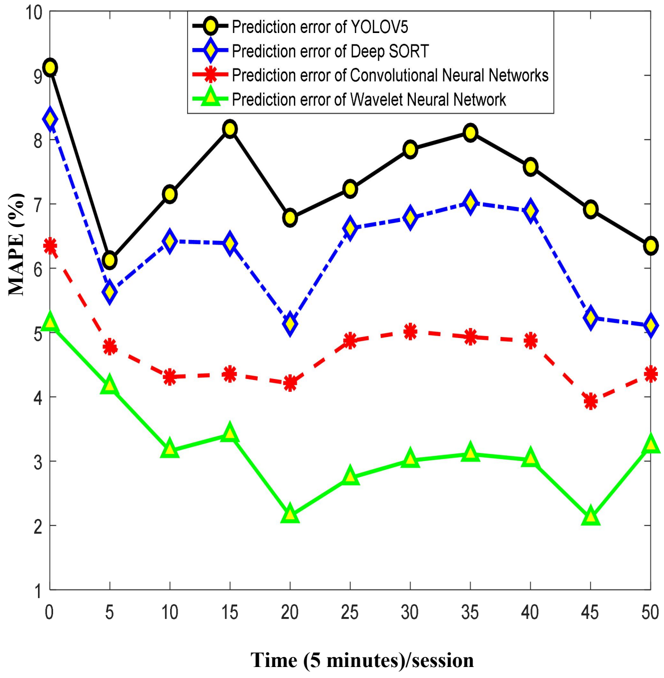
Fig. 5. Comparison of actual and predicted traffic flows every 5, 10, and 15 minutes

The traffic flow depicted in Figure 5 provides estimations for intervals of five, ten, and fifteen minutes, which closely align with the actual values. Calculations reveal that the accuracy of traffic flow projections is 93.98% for five-minute predictions, 95.24% for ten-minute predictions, and 95.42% for fifteen-minute predictions – all exceeding a threshold of 90%. Furthermore, it is observed that forecast accuracy improves as the time scale increases.

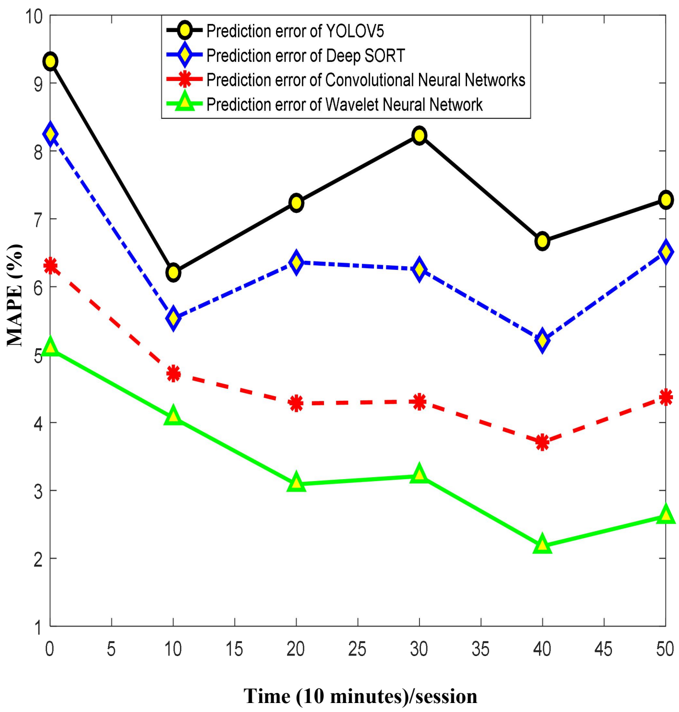
V. COMPARATIVE ANALYSIS

The wavelet neural network proposed in this paper forecasts the same dataset across various time scales. At the same time, the average absolute percentage error (MAPE) [12] is employed to quantify the prediction accuracy. This facilitates a comparative analysis of the Deep SORT prediction method [10], YOLOV5 prediction method [11], Convolutional Neural Networks (CNN) [13], and wavelet neural network (WNN) on the Traffic flow dataset [14,15,16]. These data sets comprise 18.5 hours of measurements from 190,000 vehicles at six locations, totaling 65,000 km with 6,600 complete lane changes and a positioning error of less than 10 cm. Figure 6 illustrates the anticipated outcomes.

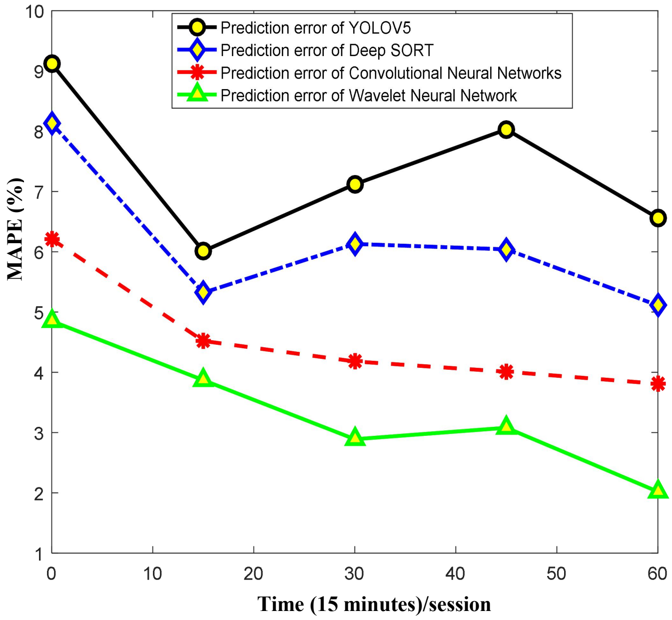
Figure 6 illustrates that the wavelet neural network consistently demonstrates lower prediction errors for the same time scale compared to the other three prediction approaches. This observation suggests that the wavelet neural network outperforms the different methods in prediction accuracy due to its ability to effectively decompose the original traffic flow signal into low-frequency and high-frequency components, allowing for more accurate predictions by utilizing different model parameters.



6(a) Comparison of four different methods for traffic flow prediction (every 5 minutes)



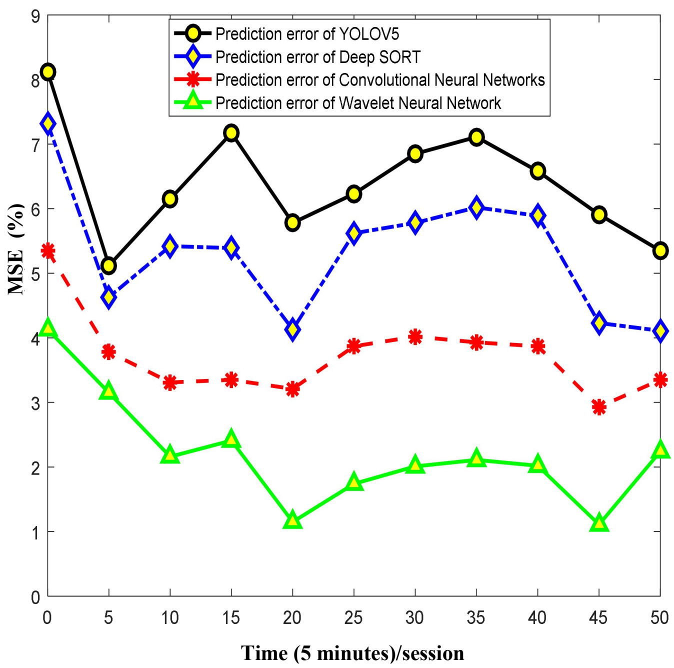
6(b) Comparison of four different methods for traffic flow prediction (every 10 minutes)



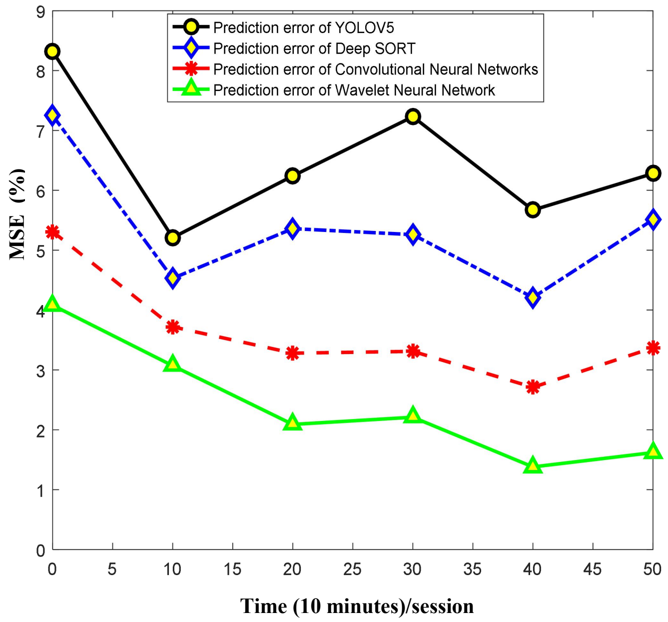
6(c) Comparison of four different methods for traffic flow prediction (every 15 minutes)

Fig. 6. Comparison results of four different methods for traffic flow prediction

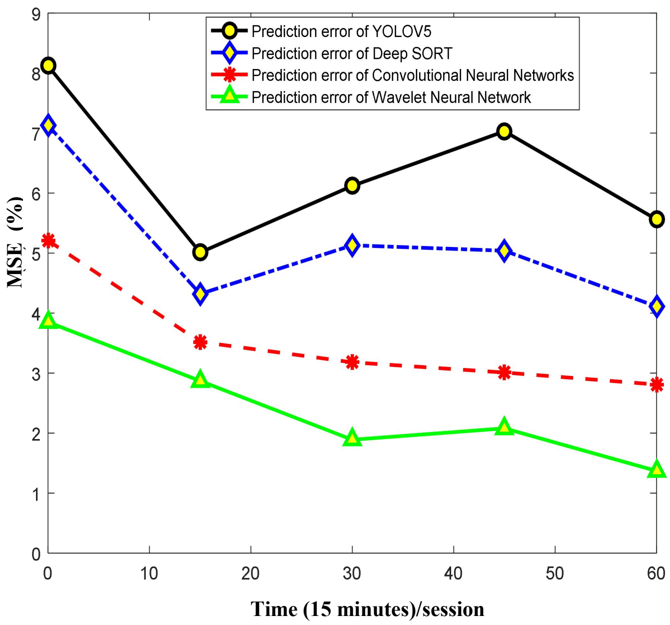
To further verify the superiority of the algorithm proposed in this paper, we selected mean square error (MSE) [17] to analyze the prediction accuracy of the four algorithms mentioned above. The comparative analysis results are illustrated in Figure 7.



7(a) Comparison of four different methods for traffic flow prediction (every 5 minutes)



7(b) Comparison of four different methods for traffic flow prediction (every 10 minutes)



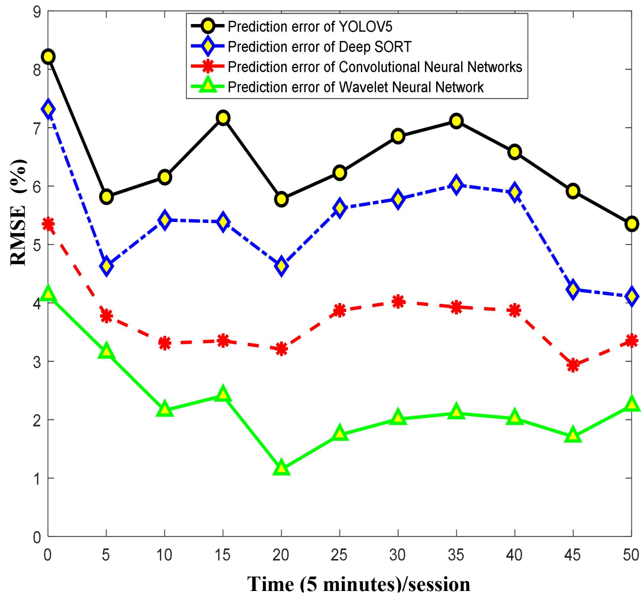
7(c) Comparison of four different methods for traffic flow prediction

Fig. 7. Comparison results of four different methods for traffic flow prediction

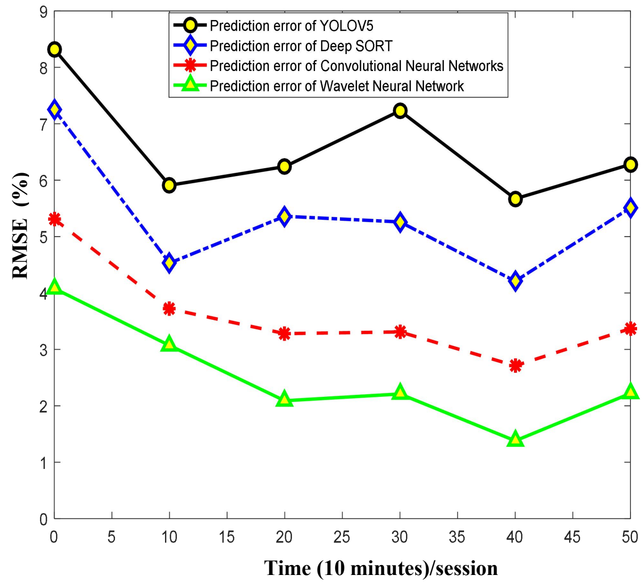
Figure 7 demonstrates that the MSE prediction error of the wavelet neural network is lower than that of the other three prediction methods at the same time scale. This once again indicates that the wavelet neural network exhibits superior prediction accuracy for traffic flow compared to other emerging prediction methods, enabling it to predict traffic flow with greater precision and speed.

To further verify the superiority of the algorithm proposed in this paper, root mean square error (RMSE) [18] is selected to compare the prediction accuracy of the four aforementioned algorithms. The comparison results are presented in Figure 8.

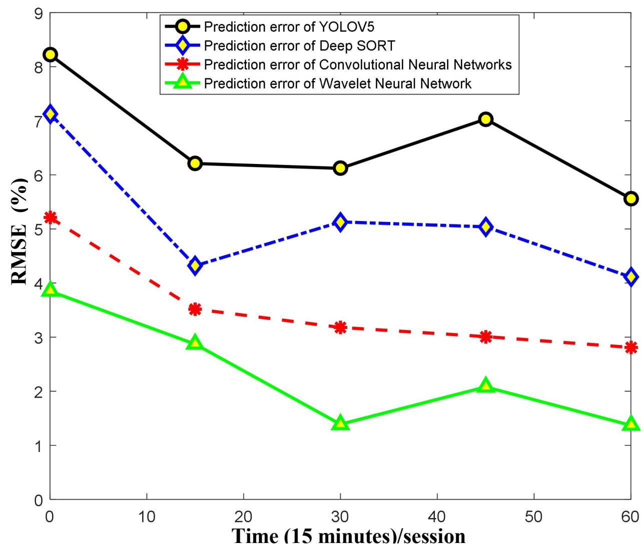
Figure 8 reveals that in comparison with other methods, wavelet neural networks possess higher prediction accuracy for traffic flow and can predict traffic flow more effectively.



8(a) Comparison of four different methods for traffic flow prediction (every 5 minutes)



8(b) Comparison of four different methods for traffic flow prediction (every 10 minutes)

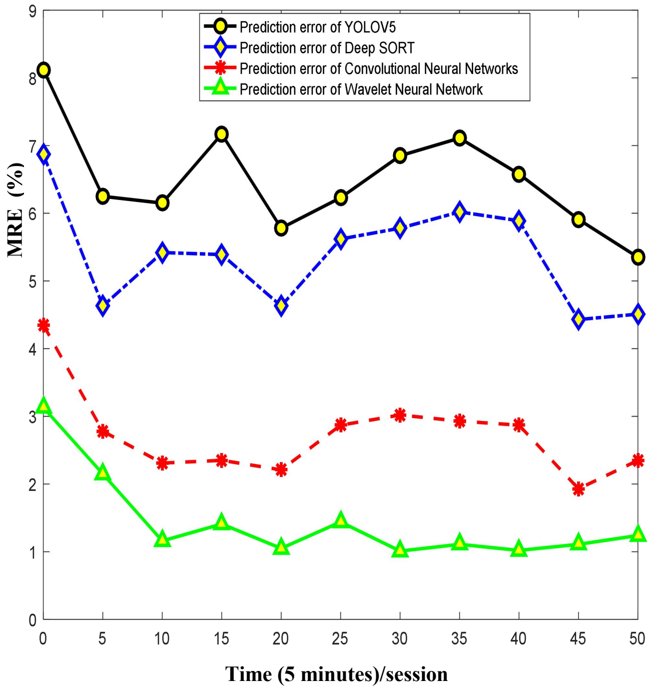


8(c) Comparison of four different methods for traffic flow prediction (every 15 minutes)

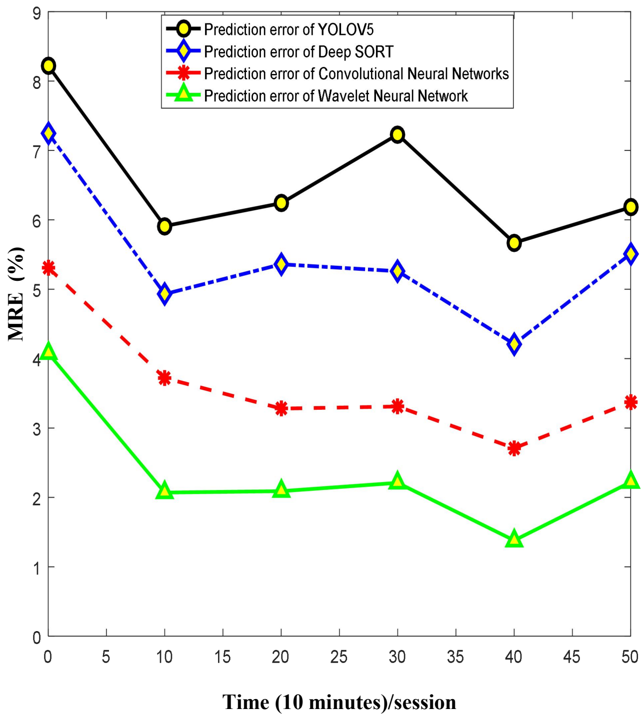
Fig. 8. Comparison results of four different methods for traffic flow prediction

To more comprehensively evaluate the prediction accuracy of the algorithms proposed in this article, the average relative error (MRE) [19] is selected to compare the prediction accuracy of the four algorithms. The comparison results are shown in Figure 9.

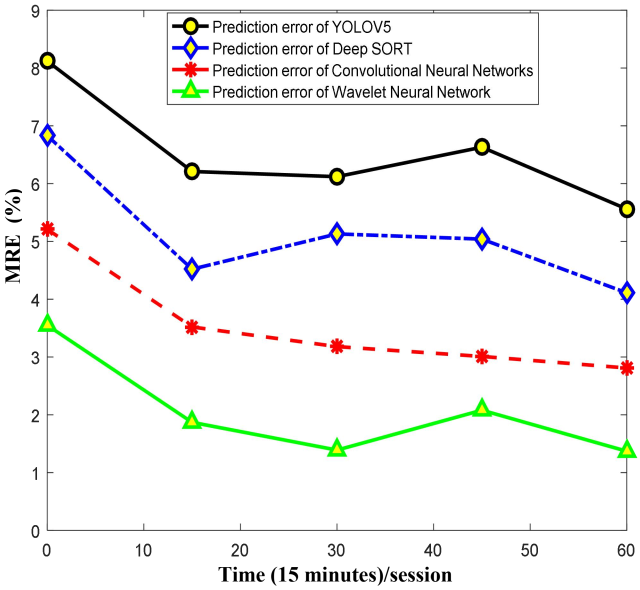
Figure 9 shows that compared with other methods, the wavelet neural network method proposed in this paper has higher prediction accuracy for traffic flow, and therefore can predict traffic flow more effectively.



9(a) Comparison of four different methods for traffic flow prediction (every 5 minutes)



9(b) Comparison of four different methods for traffic flow prediction (every 10 minutes)



9(c) Comparison of four different methods for traffic flow prediction (every 15 minutes)

Fig. 9. Comparison results of four different methods for traffic flow prediction

VI. CONCLUSION

This study proposes a wavelet neural network-based technique for traffic flow prediction, which utilizes the wavelet transform to evaluate traffic patterns. The prediction model's practical application and comparative analysis lead to the following conclusions.

1) The prediction capability of neural networks lies in their ability to decompose traffic flow into multiple signal components, enabling the identification and prediction of information components within a nonlinear system. By synthesizing data, the adverse effects of random noise on the prediction process can be mitigated, leading to more accurate final predictions.
2) The prediction accuracy of the wavelet neural network is evaluated at intervals of five, ten, and fifteen minutes by comparing the actual traffic flow values with the projected values. It has been observed that the prediction accuracy exceeds 90%. Moreover, a comparative analysis is conducted using the Deep SORT prediction method, YOLOV5 prediction method, and CNN method described in this paper. The proposed methodology demonstrates reliable anticipation of traffic flow. It enhances prediction accuracy, as evidenced by the wavelet neural network outperforming the other three approaches for the same time scale.

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