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Optimized Wavelet Neural Networks Based on Tunicate Swarm Algorithm for Short-Term Traffic Flow Prediction

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Abstract. *Short-term traffic flow prediction is an important research area in smart transportation systems. To enhance prediction accuracy, scholars have been exploring different combination models. Among these models, the wavelet neural network stands out as it combines wavelet analysis and neural networks, offering improved results in short-term traffic flow forecasting. The tunicate group optimization algorithm is another promising technique, characterized by its simplicity, efficiency, and minimal parameters required. In this study, we introduce the tunicate swarm algorithm to adjust the weights and wavelet factors of the network in the Wavelet Neural Networks (WNN) model, aiming to enhance its prediction accuracy and overall performance. We first apply wavelet analysis to distill the key features of the traffic flow data. Next, we construct the WNN model and input the traffic flow data, along with data from previous moments, for training and learning. Subsequently, we optimize the network's weights and wavelet factors using the Tunicate Swarm Algorithm (TSA), further enhancing the model's performance. Experimental findings showcase that our suggested technique attains remarkable precision and consistency in short-term traffic flow forecasting. Thus, this method holds significant value in traffic management and planning, providing practical applications for improving the reliability and accuracy of traffic flow forecasting.*
Keywords: Wavelet neural network; Tunicate swarm algorithm; Short traffic flow prediction;

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1. **Introduction.** In the recently, with the accelerating urbanization and increasing traffic flow, the need for accurate prediction of traffic flow changes has become increasingly urgent. As a significant component of traffic management and planning, short-term traffic flow prediction holds significance for enhancing the efficiency of road networks, decreasing traffic congestion, and improving the travel experience. Short-term traffic flow forecasting

focuses on forecasting traffic flow in the next few hours or days, usually based on real-time data and historical data to guide traffic management and planning decisions; The long-term traffic flow forecast pays more attention to the traffic flow forecast in the next few months or years, and usually needs to consider more factors, such as urban expansion, population growth, new roads, etc., to guide urban traffic planning and infrastructure investment decisions.

Traffic flow is influenced by diverse elements, including complex traffic networks, unforeseen events, and population changes, which makes prediction a complex and challenging task [1,2,3]. In order to tackle this problem, researchers have suggested numerous methods to enhance the accuracy and reliability of short-term traffic flow prediction. Traditional statistical and temporal models have achieved some success in prediction [4]. However, these methods often struggle to capture the nonlinear characteristics and spatio-temporal correlations present in traffic flow data. As a result, researchers have turned their attention towards deep learning methods [5,6]. The WNN, combining the strengths of neural networks and wavelet analysis, offers powerful nonlinear modeling and time-frequency feature extraction capabilities. Nevertheless, further improving the accuracy and robustness of WNN models for prediction remains a challenge. In our paper, we introduce an approach that optimizes wavelet neural networks using the Tunicate Swarm Algorithm (TSA) to tackle the aforementioned difficulties. The TSA, as an optimization technique, effectively optimizes the parameters of the WNN by iteratively searching for the best solution. By incorporating the tunicate swarm algorithm, we can enhance the performance of the WNN model and improve the accuracy and stability of prediction. To assess the efficacy of our method, we perform experiments using real traffic flow data sets. The experimental findings show that our method, which optimizes wavelet neural networks using TSA, achieves superior results in prediction compared to traditional approaches. This research provides valuable insights for traffic management and planning and has the potential to enhance the precision and reliability of traffic flow prediction in practical applications.

The layout of our paper is as follows: firstly, we introduce the related research and the current situation. Secondly, we briefly outline the evolution theory of the tunicate swarm optimization algorithm and wavelet neural networks. Next, we explain the fundamental method of optimizing wavelet neural networks using the tunicate swarm algorithm for prediction. We then conduct simulations using traffic flow data and perform comparative experiments. Finally, we conclude with a summary of our proposed method.

1.1. **Related Work.** The increasing attention in recent years towards short-term traffic flow prediction models, particularly within the realm of wavelet neural networks, has resulted in a multitude of research endeavors. Researchers have extensively explored the optimization of wavelet neural networks using intelligent algorithms to enhance the accuracy of predictions. Numerous studies have been conducted, each with its unique contribution to the field. Jiang and Adeli [7] proposed a nonparametric dynamic time-lag recursive wavelet neural network model, specifically designed for traffic flow prediction. Their approach accounted for the dynamic nature of traffic patterns, ensuring accurate predictions. Ravish and Swamy [8] introduced a novel solution for travel time prediction, emphasizing precision in their model. Saleem et al. [9] proposed a fusion-based intelligent traffic congestion control system for VNs (FITCCS-VN) using ML techniques that collect traffic data and route traffic on available routes to alleviate traffic congestion in smart cities. Hu et al. [10] optimized support vector machines using the particle swarm algorithm to predict short-term traffic flow. Their model outperformed traditional methods, such as the BP neural network and auto-regressive moving average model. Chan et al. [11] proposed a hybrid approach, combining an adaptive particle swarm optimization algorithm with neural networks and fuzzy inference for short-duration traffic flow prediction. The model was compared against the genetic algorithm, demonstrating its superior performance. Tan et al. [12] introduced a novel method based on dynamic tensor decomposition for short-duration traffic flow prediction. By effectively extracting information from traffic flow data, their model achieved accurate predictions. Other researchers applied advanced techniques to optimize wavelet neural networks. Cheng et al. [13] utilized turbulence theory and support vector machine regression to develop a multi-source traffic flow prediction method. Yang and Hu [14] enhanced the genetic algorithm with a clustering search strategy, creating the IGA-WNN model for improved accuracy. Chan et al. [15] focused on high-speed highways and employed an adaptive particle swarm optimization algorithm, combined with neural networks and fuzzy inference, for short-term traffic flow prediction. Xu et al. [16] optimized wavelet neural networks using an improved genetic algorithm, incorporating evolutionary thinking algorithms to construct the WNN model. Their approach involved refining the genetic algorithm to enhance the optimization process, resulting in more accurate predictions. In a similar vein, Chen et al. [17] also utilized an improved genetic algorithm to optimize the WNN. By incorporating evolutionary thinking algorithms, they were able to enhance the model's performance in predicting short-term traffic flow. Expanding the scope of research, Chen et al. combined fuzzy logic, wavelet transform, neural networks, and heuristic algorithms to detect traffic data trends and patterns. This approach allowed for a more comprehensive analysis of the data, leading to improved predictive capabilities. Another innovative approach was proposed by Kim and Hong [18]. They developed a hybrid mode identification model that incorporated Gaussian hybrid mode clustering and artificial neural networks. This combination enabled more accurate traffic flow predictions by considering both the specific traffic patterns and the overall flow dynamics.

Taking a different perspective, Chen et al. [19] utilized an improved TSA to optimize the wavelet neural network parameters. They found that this approach resulted in more robust and effective model training, leading to improved prediction performance. In an effort to continuously ienhance the accuracy of the prediction, Du et al. [20] applied the whale optimization algorithm to optimize the WNN for short-term traffic flow prediction. By leveraging the inherent characteristics of whale behavior, they were able to enhance the model's ability to adapt and achieve better prediction accuracy. Overall, the past decade has witnessed significant advancements in short-term traffic flow prediction using WNN. Researchers have focused on refining data processing methods, optimizing parameters through advanced intelligent algorithms, and employing novel models such as hybrid modes and optimized algorithms. These collective efforts have yielded promising results, demonstrating the feasibility and practical value of utilizing improved intelligent algorithms to optimize wavelet neural networks for short-term traffic flow prediction.

1.2. **Motivation and contribution.** Traffic flow prediction is crucial for urban traffic management and planning, as it enables authorities to develop effective strategies for reducing congestion and vehicle emissions. However, accurately predicting traffic flow in the short term poses a significant challenge. Therefore, finding an efficient and accurate method for prediction has be a current research emphasis in transportation, considering the limitations of traditional prediction methods.

This thesis aims to address this challenge by proposing a new method for short-term traffic flow prediction. The proposed method is based on optimizing the WNN using the TSA. The key contributions of this study are as follows:

(1) Introducing the tunicate swarm algorithm: the tunicate swarm algorithm is an optimization algorithm with global search ability and fast convergence characteristics. TSA can well simulate the flexible adjustment ability of biological groups. Individuals in TSA can communicate through simple vision and contact perception to explore the best solution together. This is consistent with the natural distributed cooperation mode of biological groups. The application of the TSA to the wavelet neural network is effective in optimizing network weights and thresholds, leading to improved accuracy and stability in prediction.

(2) Merging subband filtering scrutiny and neural network: wavelet analysis effectively captures spatiotemporal features in traffic flow data, and combining it with neural network can fully explore the nonlinear relationship in the data and improve the model's performance.

(3) Experimental validation and performance evaluation: the effectiveness and superiority of this approach is validated by conducting experiments on actual traffic flow data. Meanwhile, Various evaluation indexes are utilized to quantitatively analyze the prediction outcomes and evaluate the precision and dependability of the prediction model.

2. Relevant theoretical analysis.

2.1. Tunicate swarm algorithm.

The TSA is a global search algorithm influenced by the foraging conduct of tunicate animals [20, 21]. As a kind of animal that moves in the ocean with fluid jet propulsion, tunicate swarm have the ability to forage in the deep sea. But as the exact food location remains unknown, in the pre-foraging stage, tunicate swarm use individual fetching from the surrounding seawater, generating jet propulsion through the atrial siphon, which migrates to forage with the help of the strong propulsive force. Since most of the periplasmic animals are only a few millimeters in size, they often use the gelatinous perithecium to connect with each other in the late stage of food searching and use a light blue-green light to send out signals to obtain food in a clustered manner. Inspired by the foraging behavior of tunicate swarm, the tunicate swarm algorithm adopts two strategies for modeling: jet propulsion and group behavior, in which the jet propulsion phase is mainly divided into three parts: avoiding conflicts among searching individuals, moving to the optimal searchingneighbors, and converging to the optimal searching individuals. The group behavior is mainly for updating the positions of the optimal searching individuals. In the iterative search process, the bagged individual represents the possible solution to the optimization issue, and the food represents the optimal solution of the problem [23,24,25].

2.1.1. *Mathematical model of the TSA.*

The tunicate swarm use the vector $\vec{C}$ to compute a new search direction in order to avoid search individual conflicts during jet propulsion movement:

$$\vec{C} = \frac{\vec{A}}{B} \tag{1}$$

$$\vec{A} = c_2 + c_3 - \vec{T} \tag{2}$$

$$\vec{T} = 2 \cdot c_1 \tag{3}$$

where $\vec{A}$ is the gravitational force; $\vec{T}$ denotes deep-sea horizontal convection; c_1, c_2, and c_3 are random numbers ranging from 0 to 1, which denotes the interaction force between individuals. The computational expression is:

$$B = |Y_{\min} + c_1(Y_{\max} - Y_{\min})| \tag{4}$$

where $Y_{\min}$ and $Y_{\max}$ denote the minimum and maximum values of the initial interactions, which generally take the minimum value of 1 and the maximum value of 4.

After effectively avoiding the search conflict, the encapsulated individual will move towards the optimal search neighbor and use it as a guide to calculate the search distance [26, 27]:

$$PD_i = |x^f_{\text{best}} - rand \cdot x^f_i| \tag{5}$$

where t denotes the current iteration. x_{best} represents the food's location, x^f_i represents the position of the searching individual i at the t-th iteration, and rand denotes a random number that meets [0-1] uniform distribution.

Then, each searching individual gradually approaches the optimal individual position, i.e:

$$x^{f+1}_i = \begin{cases} x^f_{\text{best}} + \vec{A} \cdot PD_i, & q \geq 0.5 \\ x^f_{\text{best}} - \vec{A} \cdot PD_i, & q < 0.5 \end{cases} \tag{6}$$

where q is a random value between 0 and 1, and x^f_i denotes the position of the updated search individual.

After avoiding individual conflicts and calculating the distance between the location of the encapsulated individual and the food source, each searching individual adopts a group behavior to encircle towards the food source. For better mathematical modeling of the group row of the encapsulated individual, the group behavior is expressed as follows by saving the position information of the first two best searching individuals to update the position of the other searching individuals [28].

$$x^{t+1}_i = \frac{x^t_i + x^{t+1}_i}{2 + c_1} \tag{7}$$

2.1.2. *Pseudo-code for the TSA.* Next, we will introduce the pseudocode of our proposed algorithm, which is shown as Algorithm 1. The algorithm process is shown in Figure 1.

Algorithm 1 TSA

Input: number of population of pouch animals, n
Output: optimal value

begin
Initialize the population, set algorithm parameters, a, g, f, m, and maximum number of iterations, etc;
Calculate the fitness function values for each search individual;
Obtain the best solution by evaluating the fitness score of each pocket animal individual;
while ($t <$ maximum number of iterations) **do**
  for $i = 1$ to n **do**
    Update a, g, f, m;
    Calculate using Equation (5);
    if $rand \leq 0.5$ **then**
      $x_i^{t+1} = x'_{best} + \vec{A} \cdot PD_i^t$
    else
      $x_i^{t+1} = x'_{best} - \vec{A} \cdot PD_i^t$
    end if
    Calculate the final position of the pouch animal based on Equation (7);
  end for
  For pouch individuals outside the search space range, perform boundary handling;
  Compute the fitness for each search entity and determine the optimal solution based on their respective fitness scores.
  $t = t + 1$;
end while
Output the optimal solution;
End

2.2. **Wavelet Neural Network Predictive Modeling.** Wavelet Neural Networks (WNN) were originally proposed by the famous French information science research institute [29], and can be classified into two categories: one is the loose fusion of wavelet analysis and neural network, operating independently of each other. Network to complete the function of identification or classification; another type of tight combination, this approach involves using the wavelet function serving as the activation function for the neural network's hidden layer nodes. It harnesses the benefits of wavelet analysis while aiding in network initialization and parameter selection, but also according to the needs of the free choice of the appropriate wavelet function [30, 31], this paper adopts the tight type of WNN.

In Figure 2, the compact WNN structure is illustrated, with $\Phi(x)$ denoting the wavelet basis.

The relevant formulas for calculating wavelet neural networks are as follows:

(1) The input signal undergoes forward propagation, resulting in the computation of the WNN output value.

The output h_v of the hidden layer is calculated as follows.

$$h_v = h\left(\frac{\sum_{i=1}^{n} w_{iv} x_i - b_v}{a_v}\right), v = 1, 2, \ldots, n \tag{8}$$

where b_v indicate the wavelet basis function translation factor, a_v indicate the scaling factor of the wavelet basis function, and h_v indicate the wavelet basis.

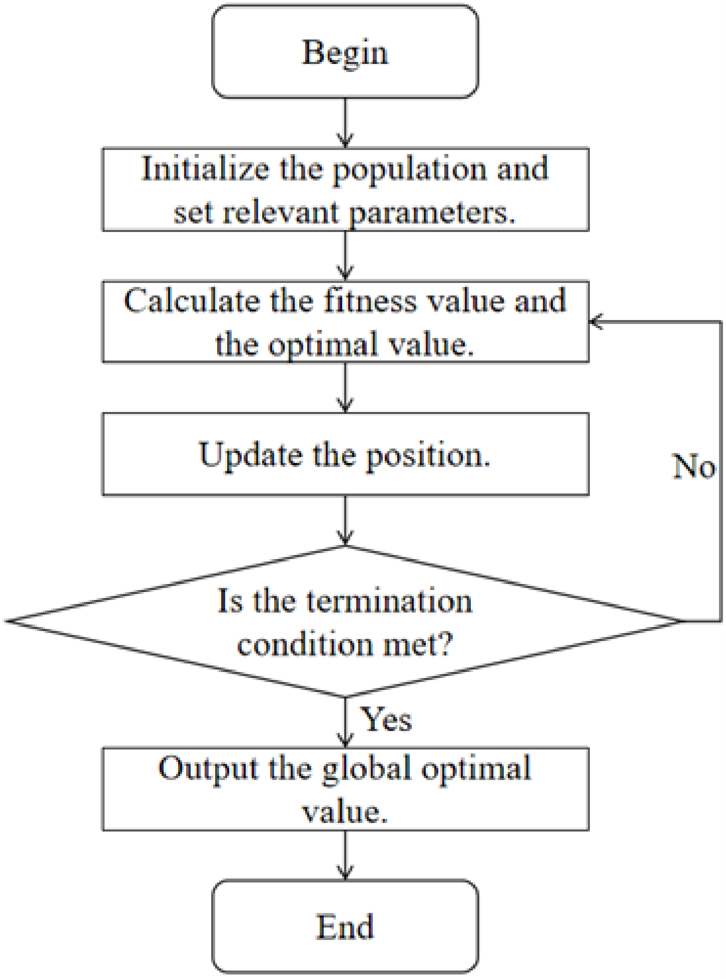

Figure 1. Flowchart of the TSA

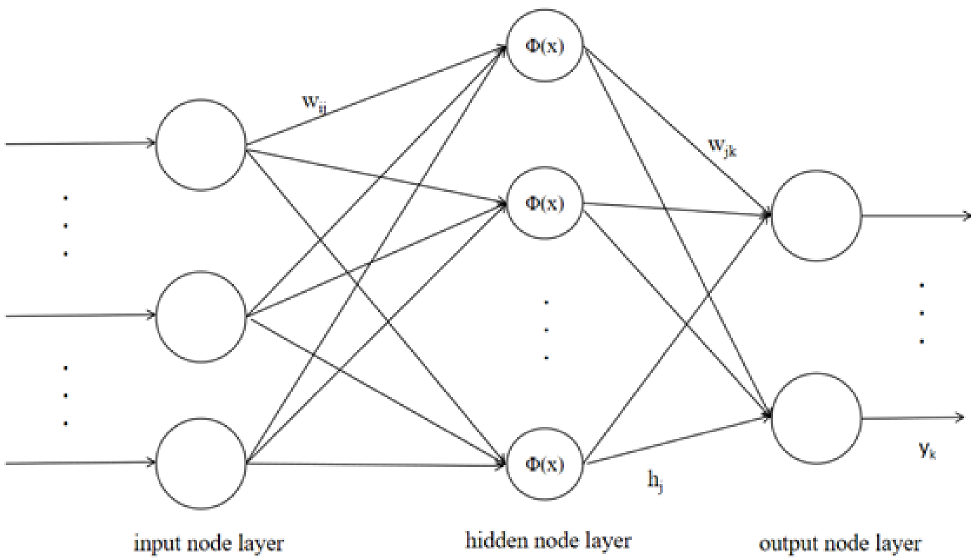

Figure 2. Structure diagram of neural network model

The output y_k of the network layer is computed as:

$$y_k = \sum_{v=1}^{n} w_{vk} h_v, k = 1, 2, \dots, m \tag{9}$$

The error between the output of the WNN and the target output is determined as follows:

$$e_k = y_k^i - y_k \tag{10}$$

The error metric function is:

$$E = \frac{1}{2} e_k^2 \tag{11}$$

(2) The error signal is propagated backwards, and the parameters are adjusted accordingly using the algorithm, and the weights and wavelet factors of the WNN are adjusted according to the E-value by the following equation:

$$w_{ij}^{(d+1)} = w_{ij}^{(d)} + \Delta w_{ij}^{(d+1)} \tag{12}$$

$$w_{jk}^{(d+1)} = w_{jk}^{(d)} + \Delta w_{jk}^{(d+1)} \tag{13}$$

$$a_j^{(d+1)} = a_j^{(d)} + \Delta a_j^{(d+1)} \tag{14}$$

$$b_j^{(d+1)} = b_j^{(d)} + \Delta b_j^{(d+1)} \tag{15}$$

where d is the number of training sessions and the adjustment is calculated as:

$$\Delta w_{ij}^{(d+1)} = -\eta \frac{\partial E}{\partial w_{ij}^{(d)}} \tag{16}$$

$$\Delta w_{jk}^{(d+1)} = -\eta \frac{\partial E}{\partial w_{jk}^{(d)}} \tag{17}$$

$$\Delta a_j^{(d+1)} = -\eta \frac{\partial E}{\partial a_j^{(d)}} \tag{18}$$

$$\Delta b_j^{(d+1)} = -\eta \frac{\partial E}{\partial b_j^{(d)}} \tag{19}$$

where η is the learning rate.

Aiming at the shortcomings and wavelet factor in the training process of slow astringent speed, the algorithm is improved, and the improved weights and wavelet factor are calculated as:

$$w_{iv}^{(d+1)} = w_{iv}^{(d)} + \Delta w_{iv}^{(d+1)} + \alpha(w_{iv}^{(d)} - w_{iv}^{(d-1)}) \tag{20}$$

$$w_{vk}^{(d+1)} = w_{vk}^{(d)} + \Delta w_{vk}^{(d+1)} + \alpha(w_{vk}^{(d)} - w_{vk}^{(d-1)}) \tag{21}$$

$$a_v^{(d+1)} = a_v^{(d)} + \Delta a_v^{(d+1)} + \alpha(a_v^{(d)} - a_v^{(d-1)}) \tag{22}$$

$$b_v^{(d+1)} = b_v^{(d)} + \Delta b_v^{(d+1)} + \alpha(b_v^{(d)} - b_v^{(d-1)}) \tag{23}$$

where α is the momentum factor, $\alpha \in [0, 1]$.

3. Short-term traffic flow prediction based on PPA-WNN.

3.1. Description of experimental data. A part of the dataset used in this paper comes from the Data Research Laboratory at the University of Minnesota Duluth [31], where all the data are collected by the Twin Cities Traffic Management Center through more than 4,500 loop detectors on the Twin Cities Telluride Highway. The other part is derived from PeMS, the California Transportation Performance Measurement System. During the experiment, the initial two-thirds of each dataset are utilized for training, while the remaining portion is designated for testing. Since the weights and the scaling and translation factors of the WNN are assigned initial values in each run, the prediction results will have some volatility. In this paper, 10 runs of each data set are averaged as the final prediction results, and simulation experiments are conducted on the data sets.

3.2. Experimental evaluation indicators. To facilitate a fair comparison of short-term traffic flow prediction effectiveness, this study presents commonly used evaluation metrics in the field, including MAPE, MAE, and RMSE.

MAPE:

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{a_i - \hat{a}_i}{a_i}\right| \times 100\% \tag{24}$$

MAE:

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|a_i - \hat{a}_i| \tag{25}$$

RMSE:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(a_i - \hat{a}_i)^2} \tag{26}$$

Where, a_i represents the prophesied input magnitude of the WNN at t, and $\hat{a}_i$ denotes the practical magnitude of the traffic flow at t. Among the above evaluation indexes, the smaller values of MAPE and RMSE represent the smaller error, i.e., the prophesied value of short-time traffic flow is closer to the actual value of traffic flow.

3.3. Algorithm flow of TSA-WNN. TSA is easy to be used in complex dynamic environments. Through the immediate response and adjustment between individuals, TSA-WNN algorithm can better adapt to the changes of the environment and find the real-time optimal solution. This is very advantageous for scenes that need to process a large amount of information in real time. The flow process of TSA-WNN is shown as follows:

1) Data preprocessing. Repair of abnormal data, wavelet noise reduction phase space reconstruction, and normalization are performed on the raw data.
2) Integrate sample data and divide it into training and testing sets.
3) Initialization of WNN parameters and parameters of the swarm algorithm.
4) Optimization of weights and wavelet factors by the swarm algorithm.
5) Assigning the optimized weights and wavelet factors to the network.
6) Wavelet neural network training, calculate the network output and error value, and adjust the weights and wavelet factors.
7) Input test samples for prediction.
8) Calculate the evaluation index and give the prediction results.

3.4. **Experimental results and analysis.** The experimental model environment is MATLAB2012a. The relevant parameters of the wavelet neural network are set as follows: wavelet neural network weights, translation factors, and expansion factors are generated randomly assigned in accordance with the normal distribution. 958 groups of training samples, 482 groups of test samples, the maximum training count iterations is set at 100, with a minimum error value of 1/10000, and the weight learning rate is 0.01, while the learning rates for translation factors and expansion factors are both set at 0.001. Additionally, the momentum factor is specified as 0.3.

Figure 3 shows the effectiveness of our suggested model. Figure 4 shows the error diagram of our proposed model.

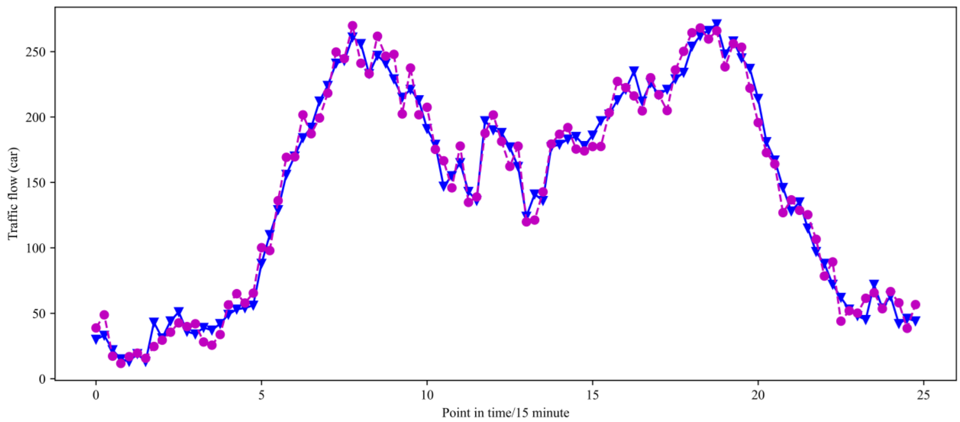

Figure 3. PPA-WNN based short-time traffic flow prediction effect diagram

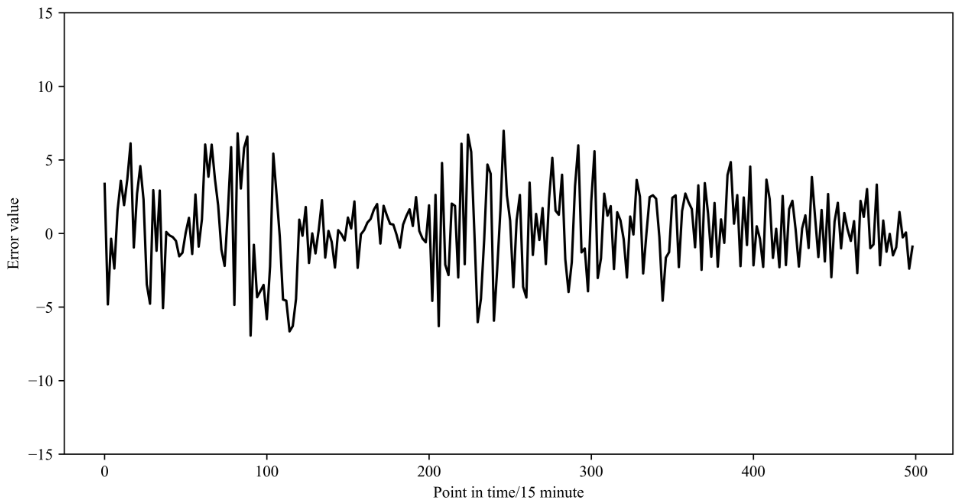

Figure 4. PPA-WNN based short-term traffic flow prediction error map

As observed in Figure 3 and Figure 4, the prediction outcomes and trends based on PPA-WNN are similar to the real values, the fluctuation of the prediction model error is small, and the forecast accuracy of the experimental data at every moment is good, which proves that our model is effective.

To demonstrate the reliability of the PPA-WNN-based short-term traffic flow prediction model in our study, Table 1 and Table 2 present the simulation results of WNN-based and PPA-WNN-based short-term traffic flow predictions for five data sets, and the average of 10 runs for each data set is taken as the most final prediction result.

Table 1. Performance results of WNN-based short-term traffic flow prediction

Dataset	MAPE	MAE	RMSE
Dataset1	0.122	1.931	2.789
Dataset2	0.505	2.054	3.152
Dataset3	0.108	10.198	15.100
Dataset4	0.074	1.443	1.949
Dataset5	0.040	12.006	14.160

Table 2. Performance results of short-term traffic flow prediction based on PPA-WNN

Dataset	MAPE	MAE	RMSE
Dataset1	0.061	1.331	2.031
Dataset2	0.440	2.083	3.167
Dataset3	0.081	9.256	12.911
Dataset4	0.053	1.088	1.484
Dataset5	0.033	9.873	12.144

Upon comparing Table 1 and Table 2, it is evident that across all datasets, the three error values have been decreased to some degree, indicating that the wavelet neural network leveraging thetunicate swarm algorithm outperforms in short-term traffic flow prediction.

4. **Summary.** This thesis centers on addressing the issue of short-term traffic flow prediction in the field of urban transportation, and proposes a new prediction model by explaining the optimization technique for wavelet neural networks bytunicate swarm algorithm. The motivation behind this article is traditional traffic flow prediction methods have certain limitations, so there is a need to find an efficient and accurate prediction method to enhance accuracy and stability of traffic flow scenario. This thesis integrates wavelet analysis and neural networks by employing wavelet analysis to derive spatio-temporal patterns from traffic flow data, which are inputted into the neural network model, so as to fully explore the non-linearity in the data. Then, the weights and wavelet factors of the network are optimized by being tunicate group algorithm to enhance the precision and stability of the forecast model. The experimental results demonstrate that the wavelet neural network method optimized using the tunicate swarm algorithm, as proposed in our study, exhibits high accuracy and stability in the prediction, which has obvious advantages over the traditional method. By merging wavelet analysis and neural networks and optimizing the model with the TSA, this method notably enhances the precision and stability of traffic flow forecast. This will play a positive role in improving urban traffic management and planning, and has important practical application value.

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