Short-term Traffic Flow Prediction Based on Harmony Search Algorithm Optimized Wavelet Neural Network

Guifang Shen
Anhui Institute of Public Security Education, Hefei 230031, China
sgf1979@xy.hfut.edu.cn
308368591@qq.com

Abstract. In order to improve the prediction accuracy of urban road short-term traffic flow, this paper proposes a short-term traffic flow prediction model of wavelet neural network optimized by harmony search algorithm (HS-WNN), to solve the problem of slow convergence speed and local optimization when the traditional wavelet neural network one-way gradient descent method is used for parameter optimization. The harmony search algorithm is used to optimize the parameters of the wavelet neural network, and the obtained optimal solution is used to optimize the initial value of the wavelet neural network model, and to predict the short-term traffic flow. And through the simulation experiment of the measured traffic flow data, it is verified that the prediction error of the HS-WNN in this paper is smaller than that of the WNN, HS-WNN has a higher accuracy.

1. Introduction

The increasing number of motor vehicles makes traffic congestion more and more serious. In order to alleviate traffic congestion and achieve efficient operation of vehicles, traffic control strategies and intelligent traffic flow guidance are very necessary in the context of intelligent transportation [1], and the prediction of traffic flow is an indispensable part of intelligent traffic control. Therefore, this article focuses on the prediction of traffic flow.

In the research of traffic flow prediction currently, the prediction with a general time span of less than 15 minutes is called short-term traffic flow prediction. In recent years, many scholars have carried out research on short-term traffic flow prediction algorithms. Among them, BP neural network and wavelet neural network model are widely used. Literature [2] optimized the weights and thresholds of wavelet neural network based on artificial bee colony algorithm, constructed a short-term traffic flow prediction model, and verified the effectiveness of the model through experiments. Literature [3] combines the wolf pack algorithm with the gradient descent algorithm, first improves the wolf pack algorithm, and then uses the improved wolf pack algorithm to find a set of better weights and wavelet factors for the wavelet neural network, based on the optimized WNN prediction Short-term traffic flow. Literature [4] uses differential evolution algorithm to optimize artificial bee colony algorithm, and is used to optimize the parameters of wavelet neural network, and then applied to the prediction of short-term traffic flow. Literature [5] proposed an improved particle swarm algorithm to optimize the wavelet neural network prediction model, and applied the model to short-term traffic flow prediction. The above studies have made some progress in traffic flow forecasting. However, due to the complexity, strong nonlinearity and uncertainty of traffic flow data, it is difficult...
for a single model to predict it comprehensively and accurately, and a combined prediction model can achieve better results.

This paper proposes a short-term traffic flow prediction model based on Harmony Search Algorithm (HSA) [6] optimized wavelet neural network (HS-WNN). The harmony search algorithm is used to optimize the connection weights, expansion factors and translation factors of the wavelet neural network, thereby making up for the random defects of the wavelet neural network parameter selection, and it is verified that the HS-WNN model has better convergence ability and better prediction accuracy through simulation experiments which is applied to short-term traffic flow prediction comparing the WNN model.

2. Wavelet Neural Network and Harmony Search Algorithm

2.1. Wavelet Neural Network

Wavelet Neural Network (Wavelet Neural Network, WNN) can be regarded as a function connection network based on wavelet function or RNF network extension, and its basic structure is shown in Figure 1. However, compared with general feedforward networks and RBF networks, WNN has the advantages of strong adaptability, simple network structure, and good fault tolerance. WNN is established based on the BP neural network structure, in which the transfer function of the hidden layer node is the wavelet basis function. At the same time, the initial parameters of the neural network wavelet function are optimized by using the error back propagation.

Fig.1 Topology of WNN

In Figure 1, $x_j$ is the input vector, $h_j$ is the hidden layer output, $y_k$ is the output vector, $m$ is the number of input layer nodes, $s$ is the number of hidden layer nodes, $n$ is the number of output layer nodes, and $h(j)$ is the wavelet basis Function, $w_{ij}$ is the connection weight between the input layer and the hidden layer, and the hidden layer, $w_{jk}$ is the connection weight between the hidden layer and the output layer node. The output of the hidden layer can be expressed as follows:

$$h(j) = h \left( \frac{\sum_{i=1}^{m} w_{ij} x_i - b_j}{a_j} \right), \ j = 1, 2, \ldots, s$$ (1)

Among them, $a_j$ is the expansion factor of the wavelet basis function, $b_j$ is the translation factor of the wavelet basis function, and the Morlet wavelet basis function selected by $h(j)$ is used as the transfer function of the hidden layer node:

$$y = \cos(1.75x)e^{-x^2/2}$$ (2)

The output of WNN can be expressed as:

$$y(k) = \sum_{j=1}^{s} w_{jk} h(j), \ k = 1, 2, \ldots, n$$ (3)

2.2. Harmony Search Algorithm

Harmony search algorithm is a meta-heuristic algorithm originated from imitating the process of music creation. With simple structure and strong global search ability, it has been applied to non-linear
multi-objective optimization problems, classification, and engineering applications in medical, robotics, and communication problems [7].

HSA first randomly generates a harmony memory bank, selects a new harmony in the harmony bank with the probability of the harmony memory reference rate \( HMCR \), and fine-tunes it with a certain probability; selects a new harmony in the feasible region with the probability of \((1-HMCR)\). Then compare the new harmony with the harmony in the harmony memory, eliminate the worst harmony and update the harmony memory.

Candidate solutions \( X' = \{x'_1, x'_2, \cdots, x'_J\} \) are generated by the following rules:

1. Randomly select a new harmony in the harmony memory:

   \[
   x'_j = \begin{cases} 
   x_{\text{rand}(i),j}, & \text{Rnd} < HMCR \\
   x_j \in \Omega_j, & \text{otherwise}
   \end{cases}
   \]  

   Among them: \( x_{\text{rand}(i),j} \) represents the randomly selected variable of the first harmony in the harmony memory bank, \( x_j \in \Omega_j \) represents a random value within the value interval of the variable, is the selection probability, represents a uniformly distributed random number on.

2. Fine-tuning of candidate solutions

   \[
   x'_j = \begin{cases} 
   x'_j + bw, & \text{Rnd} < PAR \\
   x'_j, & \text{otherwise}
   \end{cases}
   \]  

   Among them: \( bw \) is the amount of fine adjustment, and \( PAR \) is the probability of fine adjustment.

3. Harmony Search Algorithm Optimizes Short-term Traffic Flow Prediction Based on Wavelet Neural Network

The process of optimizing the wavelet neural network prediction model based on the harmony search algorithm includes three parts: traffic flow data preprocessing, HS algorithm to obtain the optimal solution, and WNN prediction model establishment: the structure of the WNN neural network is determined according to the input and output parameters, so as to determine each The code length of the individual harmony. Each individual in the population contains the weights, expansion factors and translation factors in the WNN prediction model.

The main steps are as follows:

1. Import the collected data set first, and preprocess the data set, including missing and abnormal data repair, data noise reduction, reconstruction and normalization processing.

2. Initialize the parameters of the harmony memory bank and the harmony search algorithm, encode the WNN parameters to be optimized, and determine the dimensions of the individual harmony. Each harmony individual contains all the parameters in the WNN prediction model, including the weight between the WNN input layer and the hidden layer, the weight between the hidden layer and the output layer, the translation factor and the expansion of the wavelet basis function The sum of the number of factors.

3. Generate new harmony: through formula (4)(5), generate new harmony.

4. Update the harmony memory. Calculate the fitness function value of the new harmony, eliminate the worst harmony, and update the harmony library based on the best.

5. Determine the termination condition of the algorithm. If the current number of iterations is equal to the maximum number of iterations, the operation will be terminated; otherwise, repeat 3 and 4.
⑥ Decode the optimized harmony and assign it to the corresponding parameters of the WNN network model.

⑦ Train the WNN based on the training data set, and calculate the network output value and error value.

⑧ Use gradient descent algorithm with dynamic factor to adjust WNN parameters until the end condition is met.

⑨ Input the test data into the trained HS-WNN model for prediction, obtain the prediction result, and compare the actual output with the predicted output to calculate the error.

4. Experimental design and analysis

The HS-WNN model proposed in this paper is applied to the prediction of short-term traffic flow and compared with the short-term traffic flow prediction model based on WNN to verify its performance.

The experimental simulation environment is: 64-bit Windows 8.1 operating system, Intel(R) Core(TM)i5-4210U CPU@1.70GHz 2.39GHz, 4.00GB memory. Use Matlab R2013a software to realize algorithm programming.

4.1. Data sampling and processing

The traffic flow data in this experiment comes from the measured data from a highway observation station, and the total observation time is 96 hours for 4 consecutive days. According to the time interval characteristics of short-term traffic flow, the number of vehicles at an interval of every 15 minutes is recorded, and a total of 380 sets of data are obtained. Take the first 288 sets of data of this data set as training samples, normalize these data as the network input, and the last 92 sets of data as test samples.

The wavelet neural network structure used in this experiment is 4-7-1: the input layer has 4 nodes, representing the traffic flow at the 4 time points before the predicted time node; the hidden layer has 7 nodes (determined based on empirical values combined with experiments); one node in the output layer is the traffic flow predicted by the network. The initial parameters of WNN are the optimal values optimized by HS.

4.2. Experimental parameter settings

The HS algorithm parameter setting is shown in Table 1. The parameter setting of wavelet neural network is shown in Table 2. The number of input layer nodes of wavelet neural network is m, the number of hidden layer nodes is s, and the number of output layer nodes is n. According to the 4-7-1 structure of WNN determined in this experiment, according to the structure of wavelet neural network in Figure 1, it is obvious that you need to optimize The number of variables is $m \times s + s \times 3$. From this, it can be calculated that the number of variables to be optimized in the prediction model, that is, the number of decision variables in the harmony search algorithm, $N_{VAR} = 4 \times 7 + 7 \times 3 = 49$.

| Parameter Name | Parameter Description               | Value |
|----------------|------------------------------------|-------|
| $HMS$          | Harmony library size               | 30    |
| $HMCR$         | Harmony memory retention probability| 0.9   |
| $PAR$          | Probability of pitch adjustment    | 0.35  |
| $bw$           | Adjustment step                    | 0.1   |
| $T$            | Algorithm iterations               | 5000  |

Tab.1 Parameter settings for the HS algorithm

| Parameter Name                        | Value   |
|---------------------------------------|---------|
| Maximum number of training            | 100     |
| Minimum error                         | 0.00001 |
| Weight learning rate                  | 0.01    |

Tab.2 Parameter Settings for the WNN
4.3. Experimental results and evaluation analysis
The curve comparison of the network evolution process of WNN and HS optimized wavelet neural network is shown in Figure 2. Figure 2 shows that the convergence speed and optimization accuracy of HS-WNN are better than WNN under the premise of setting the same values of WNN parameters for the two methods.

![Network Evolution Curves Comparison of WNN and HS-WNN](image)

Fig.2  Network Evolution Curves Comparison of WNN and HS-WNN

The prediction results of WNN and HS-WNN for 92 sets of data samples and the comparison with actual traffic flow data are shown in Figure 3 and Figure 4. Among them, the HS-WNN model has a higher degree of fit between the traffic flow prediction curve and the actual traffic flow curve than WNN.

![Comparison of predicted traffic flow of WNN and actual data](image)

Fig.3 Comparison of predicted traffic flow of WNN and actual data
Fig. 4 Comparison of predicted traffic flow of HS-WNN and actual data

In order to quantitatively analyze the prediction effect, this paper selects four indicators, namely the average absolute error MAE, the average relative error MRE, the mean square error RMSE, and the degree of fit EC, to evaluate the prediction results [8].

| Model   | MAE   | MRE   | RMSE  | EC   |
|--------|-------|-------|-------|------|
| WNN    | 32.223| 0.856 | 0.946 | 0.792|
| HS-WNN | 18.543| 0.434 | 0.488 | 0.912|

Table 3 shows the MAE, MRE, RMSE and EC of the two model training results. The data shows that the MAE and MRE of HS-WNN are lower than those of WNN, which effectively verifies the impact of the algorithm on the prediction accuracy when optimizing the initial parameters of WNN. In addition, the EC value of HS-WNN is greater than 0.9, indicating that HS's optimization of the initial parameters of WNN can accelerate the network convergence speed and avoid local optimization, thereby improving the curve fitting ability to a certain extent.

The comparison of the prediction errors of the two models is shown in Figure 5. Figure 5 shows that the average error and maximum error of HS-WNN are smaller than WNN, indicating that the prediction of HS-WNN is more stable and more accurate.

Fig. 5 Prediction Error Comparison Curves of WNN and HS-WNN
5. Conclusion
Aiming at the problems of wavelet neural network's random initial weights and factors that easily lead to slow network learning and easy to fall into local solutions, this paper proposes a short-term traffic flow prediction model that optimizes the parameters of wavelet neural network by harmony search algorithm. The algorithm uses wavelet neural network as the basic framework, and uses the harmony search algorithm to optimize the connection weight of the wavelet neural network and the initial value of the expansion factor and translation factor of the wavelet basis function, which improves the convergence speed and prediction accuracy of the network. Simulation experiment results based on short-term traffic flow show that the HS-WNN model has higher convergence speed and prediction accuracy.

Acknowledgments
This work was financially supported by the Key Natural Science Foundation of Education Department of Anhui Province under Grant No. KJ2019A0891, KJ2019A0877.

References
[1] Zhao Na, Yuan Jiabin, Xu Han. Overview of Intelligent Transportation System[J]. Computer Science, 2014, 41(11):7-11.
[2] Cao Li. Research on Short-term Traffic Flow Forecast Based on Improved Wavelet Neural Network[J]. Journal of Sichuan University of Science & Technology: Natural Science Edition, 2015(28): 52-57.
[3] Qi Lu. Wavelet neural network short-term traffic flow prediction based on improved wolf pack algorithm [D]. Chengdu: Southwest Jiaotong University, 2017.5.
[4] Huang Entan, Gu Yuanli. Short-term traffic flow prediction based on improved artificial bee colony algorithm and optimized wavelet neural network[J]. Shandong Science, 2018, v.31; No.151(02):83-91.
[5] Ma Meiqin, Li Fengjun, Zhao Juping. Short-term traffic flow prediction based on improved particle swarm optimization optimized wavelet neural network [J]. Journal of Ningxia Normal University, 2019, 40(01): 73-79.
[6] Geem Z W, Kim J H, Loganathan G V. A new heuristic optimization algorithm: Harmony search[J].Simulation,2001, 76(2): 60-68.
[7] Zhou Yalan,Huang Tao. Improvement and application of harmony search algorithm[J].ComputerScience,2014,41(6):52-57.
[8] HONG H, HUANG W, ZHUO X, et al. Short-term traffic flow fore-casting: multi-metric KNN with related station discovery[C].Zhangjiagie:International Conference on Fuzzy Systems & Knowledge Discovery, 2016.