Allication of wavelet neural network to forecast of urban water demand in Maoming

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Abstract

The forecast model of water demand in Maoming urban based on wavelet neural network is presented in this paper. And it is used in the forecast of urban water demand in Maoming. The numerical results show that the wavelet neural network model has higher forecast precision compared with the predicted outcomes of the BP network.

Keywords

BP neural network, wavelet neural network, urban water demand in Maoming

1. Introduction

With the construction of the city's Binhai New Area in Maoming, the city's main urban expansion is imperative. Water as a basis for the construction of urban facilities, if predict future water needs, optimal scheduling of water resources which is the premise and foundation. Currently on water demand forecasting methods, the research literature mostly used regression forecasting, gray Markov prediction and so are several methods. Traditional modeling methods due to the time series stations, normality, independence and other restrictions, the time series are not suitable for complex water demand. The rapid development of information technology and artificial intelligence technology for water demand modeling and forecasting provides many new methods. Traditional BP neural network is a multilayer feed forward neural network before, because of its simple structure, training algorithm and more maneuverability good, BP neural network has been widely used[1]. Theoretical studies have shown that long as it has enough hidden layer neurons, three artificial neural networks can be infinitely close to any time sequence and function. The back propagation (BP) neural network has large-scale computing capability and can easily perform the nonlinear mapping process, which is a unique advantage when dealing with large complex nonlinear systems. However, BP has some limitations. For example, BP easily falls into the local minimum and has a fixed learning rate[2].

Wavelet analysis is a new mathematical method of the mid-1980s developed, which is the time - frequency analysis in the field of a new technology[3]. The basic idea is similar to the Fourier transform of wavelet analysis. And the projection function characterization is signal on a cluster basis functions spanned space. Artificial Neural Network (Artificial Neural Network, ANN) is in understanding human brain on the basis of mathematical and physical methods and the processing of information from the perspective of the human brain biological neural networks set up some kind of abstract and simplified model. It is in some way connected to each other by a plurality of processing units and a very simple form, the system is by its state of the external input dynamic response information to process information. Since the wavelet transform to reflect local characteristics of the signal frequency and focusing characteristics, and the neural network has self-learning, adaptive, robust, fault-tolerance capabilities in signal processing[4]. How to combine the advantages of both has been a concern, and wavelet neural network wavelet analysis and neural network is a combination product[5].

Wavelet neural network fully inherited both wavelet analysis and neural network advantages. On the other hand, wavelet analysis donates considerable insight into the physical form of the data by presenting information in both time and frequency domains of the time series[6]. It has been found that a proper data pre-processing which uses wavelet analysis can cause the models to adequately describe the real characteristics of the basic system. The wavelet transform has enlarged in occupation and popularity in recent years since its inception in the early 1980s, yet still does not enjoy the wide spread usage of the Fourier transform. Fourier analysis has a serious disadvantage. In transforming to the frequency domain, time information is lost[7]. When looking at a Fourier transform of signal, it is impossible to tell when a particular event took place but wavelet analysis allows the use of long time intervals where more precise low-frequency information and shorter regions are necessary where high-frequency information is wanted[8]. In the field of earth sciences, Grossmann and Morlet who worked especially on geophysical seismic signals, introduced the wavelet transform application. As there are many good books and articles introducing the wavelet transform, this paper will not delve into the theory behind wavelets and only the main concepts of the transform are briefly presented.

The remainder of this paper is organized as follows: in section 2 the Wavelet neural network is described. And in section 3 the numerical results of the algorithm is presented. In section 4 we conduct our conclusions.

2. Wavelet neural network

2.1 Construction of wavelet neural network model

Wavelet analysis and neural network currently there are two main binding ways: one is "loose", which is to use wavelet analysis of signal preprocessing, and then into the neural network processing; the other is a "compact type", such as Figure 1 shows that the wavelet neural network (wavelet neural network) or wavelet network, which is a new neural network model combining the wavelet transform theory and neural network constructed[9]. The method is to pass the neural network hidden layer neuron excitation functions using wavelet function instead, fully inherited the wavelet transform good time-frequency localization properties of neural networks and self-learning function, it is widely used in signal processing , data compression, pattern recognition and fault diagnosis and other fields. "Compact type" wavelet neural network has better data processing capability, is research on wavelet neural network. The network structure of wavelet neural network is showed below:

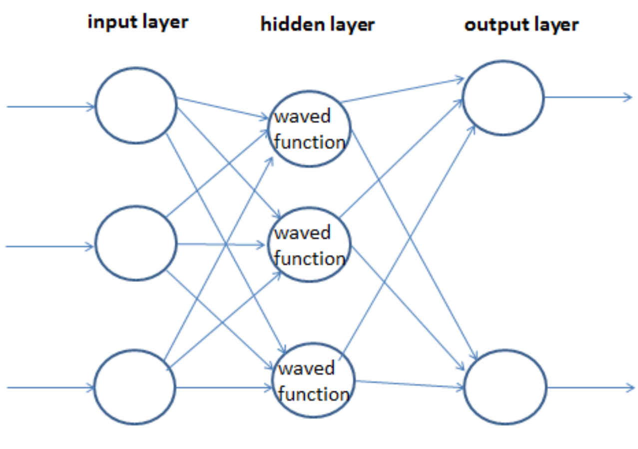

Fig1. the structure of wavelet neural network

In the sequence of the input signal $x_i(i=1,2,\cdots,k)$, the output of the hidden layer is calculated as:

$$h(j)=h_j\left(\frac{\sum_{i=1}^{k}\omega_{ij}x_i-b_j}{a_j}\right) \qquad j=1,2,\cdots,l \tag{1}$$

In this equation, the output value for the first node hidden layer is $h(j)$, ω_{ij} are network weights, b_j is shift factor of wavelet function, a_j is a stretching factor of wavelet function and h_j is a wavelet function. The wavelet function in the model is used for the Morlet wavelet function, the equation formula is as follows:

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

And the wavelet neural network output layer is calculated as follows:

$$y(k) = \sum_{i=1}^{l} \omega_{ik} h(i) \quad k = 1, 2, \cdots, m \tag{3}$$

Here, ω_{ik} are network weights, $h(i)$ represents the value of the output node, l is the numbers of hidden layer, m is the numbers of output layer.

One of the advantages of wavelet transform lies in its ability to extract multiscale information from the input data. By recursively applying wavelet transforms, it leads to multi-level wavelet decomposition. The wavelet neural network correction procedure is as follows.

Step 1: Calculate the error between network forecast output and expectation output.

$$e = \sum_{k=1}^{m} yn(k) - y(k) \tag{4}$$

where $yn(k)$ represents the expectation output, and $y(k)$ represents the forecast output.

Step2: Follow the error to adjust wavelet neural network weights and wavelet Coefficients.

$$\omega_{n,k}^{(i+1)} = \omega_{n,k}^{i} + \Delta\omega_{n,k}^{(i+1)} \tag{5}$$

$$a_k^{(i+1)} = a_k^{i} + \Delta a_k^{(i+1)} \tag{6}$$

$$b_k^{(i+1)} = b_k^{i} + \Delta b_k^{(i+1)} \tag{7}$$

Here $\Delta\omega_{n,k}^{(i+1)}$, $\Delta a_k^{(i+1)}$, $\Delta b_k^{(i+1)}$ is calculated according to the expected error.

$$\Delta\omega_{n,k}^{(i+1)} = -\eta \frac{\partial e}{\partial \omega_{n,k}^{(i)}} \tag{8}$$

$$\Delta a_k^{(i+1)} = -\eta \frac{\partial e}{\partial a_k^{(i)}} \tag{9}$$

$$\Delta b_k^{(i+1)} = -\eta \frac{\partial e}{\partial a_k^{(i)}} \tag{10}$$

where η is learning rate.

The learning process of wavelet neural network is as in the following:

Step1: Initialize parameters a_j and b_j ,while, a_j and b_j values are calculated in equation (1).

Step2: Initialize the network weights ω_{ij} and ω_{jk}, and set η.

Step3: Train the wavelet neural network. The sample is divided into training and testing samples, it is used to train the network, testing samples for testing network prediction accuracy.

Step4: Calculate the error between network forecast output and expectation output, and follow the error to adjust the network weights.

Step5: Analyzing network training is finished, otherwise, go to Step 3, if so, to predict the output of simulation results.

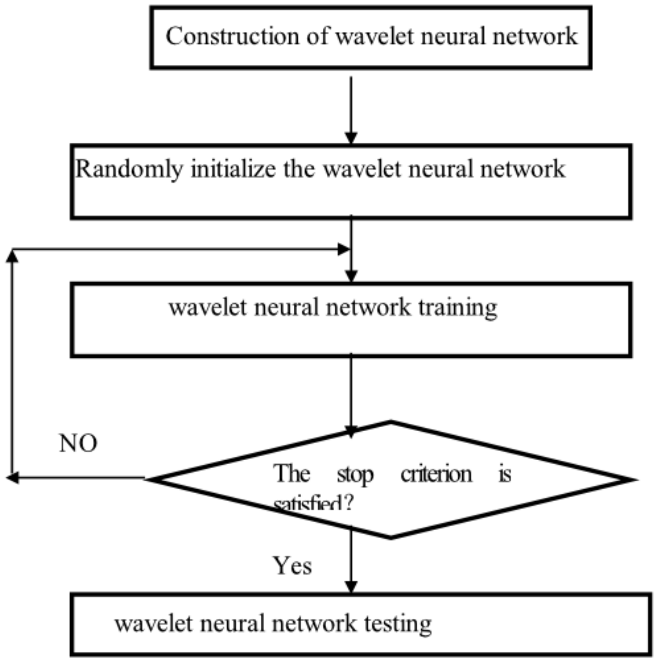

Fig2. Chart of wavelet neural network

3. Simulation experiment

In order to verify the effect of a combination of model predictions in Maoming urban water demand, the water demand data used in this paper are from 1996-2015,"Maoming Economic Yearbook", the data are shown in Table 1.

Table 1: Urban water demand in Maoming (Units: ten thousand tons)

year	Water demand	year	Water demand	year	Water demand
1996	4927.5	2002	5574.4	2008	6876.8
1997	5065.6	2003	5824.6	2009	7219.4
1998	5114.1	2004	6076.1	2010	7679.6
1999	5215.6	2005	6273.5	2011	7869.2
2000	5356.5	2006	6485.7	2012	8153.6
2001	5465.1	2007	6623.5	2013	8577.5

The utilized data were normalized due to the fact that the model training process could be speeded up by normalizing the input and target data before training. In this study, the input and target data were normalized to scale data between 0 and 1 as:

$$s_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{11}$$

Regarding the equation (11), x_i is the desired variable value, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values, respectively. s_i is the normalized variable.

Utilization of normalizing approach and transferring data between [0,1] causes that a small change in $s_{\max}$, that is the upper bound of the normalized interval and it impacts on a normalized input in the mentioned range, subsequently the normalized input has a greater influence on the output, also normalizing makes the training of the wavelet neural network more quickly.

In this paper, water demand data is divided into two parts, 1996-2008 As a training sample, and 20 09-2013 as a test sample. To illustrate through wavelet neural network model has a more accurate prediction accuracy, we use wavelet neural network model as a comparison model, using the same training set for each network training, then use the same set of tests for each network testing. Two Neural network topologies are 1-3-1, which are used there is momentum gradient descent training algorithm, the training required accuracy is 0.0001. Application of MATLAB neural network toolbox, we set the wavelet neural network learning rate $\eta = 0.02$ and a momentum factor $aerfa = 0.635$. Wavelet neural network is reached at step 212 training accuracy requirements, while BP neural network is trained only achieve accuracy requirements in step 550.The specific prediction results are presented.

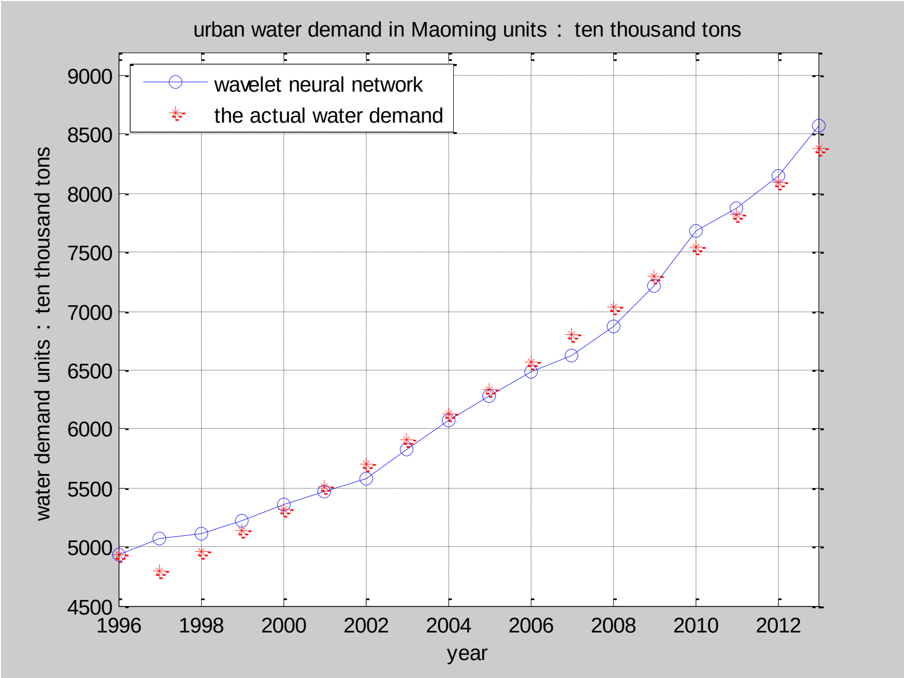

Fig.3 wavelet neural network fitting figure

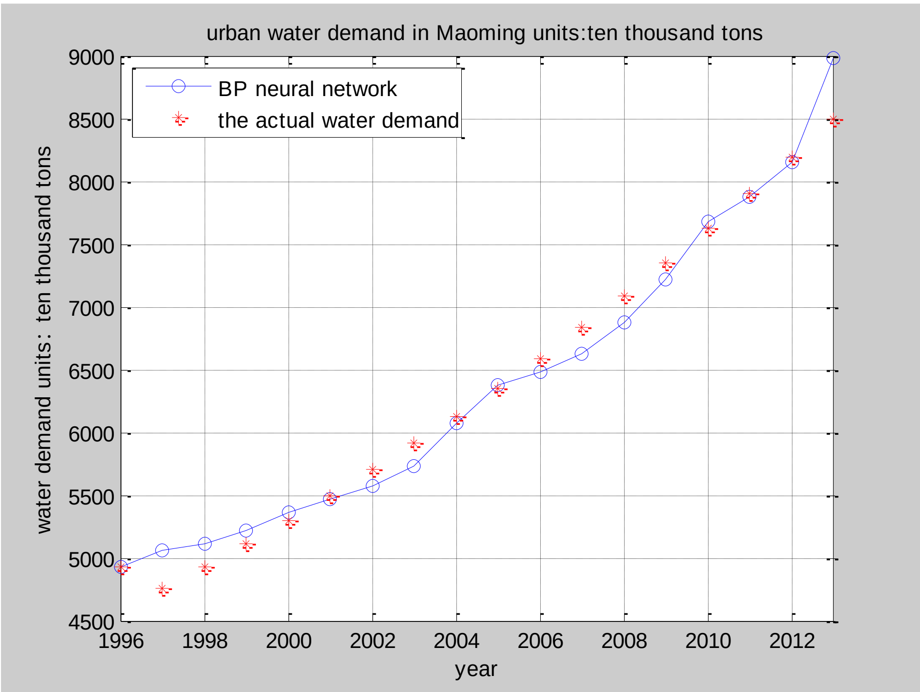

Fig.4 BP neural network fitting figure

Table2: Comparative results

actual value 2009—2013	BP neural network		Wavelet neural network	
	predictive value	relative error（%）	predictive value	Relative error（%）
7219.4	7456.6	3.28	7287.8	0.95
7679.6	7810.8	1.71	7628.2	0.67
7869.2	7923.3	0.68	7976.7	1.36
8153.6	8290.7	1.68	8267.9	1.41
8577.5	9095.8	6.04	8510.6	0.78

It can be seen from Figure 3, Figure 4 and Table2, the predict curve fitting degree of wavelet neural network is better than BP neural network. It can better tap the changing demand for water. Based on the error, the wavelet neural network model is smaller than the BP neural network.

4. Conclusion

In this paper, the wavelet neural network model is established. Comparing with the BP neural network, the results demonstrated the wavelet network has better approximation ability and prediction accuracy. Wavelet neural network fully inherited both wavelet analysis and neural network advantages.

Acknowledgements

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