Art Economic Difference Between Northern and Southern taking Beijing and Guangzhou for Example

Feng Tian

University of Science and Technology Liaoning, Liaoning Anshan, 114051 China

Abstract
In order to solve defects of neural network prediction for art economic predication, In view of the defects of the prediction model based on neural network, such as when doing prediction of nonlinear sequence, it is likely to fall into local hypo-strong point, and the rate of training is very slow, this paper proposes a prediction model based on the traditional prediction model using neural network and we use it in prediction of art economic predication, a new prediction model is formed, namely the prediction model based on wavelet neural network. The design of prediction model based on wavelet neural network, the simulation model and the simulation arithmetic are presented the paper. The prediction effect of wavelet neural network prediction model is proved in matlab 7.0 simulation environment. Finally, the model is used in predicting art economic predication. A better prediction result is gained, and the defect of falling into local hypo-strong point is overcome, the experimental results showed that the proposed method can significantly improve training's speed, prediction accuracy and prediction efficiency, and outperform neural network for art economic predication.
Keywords: ART ECONOMIC PREDICATION COMPACTNESS, CONVERGENCE, WAVELET FUNCTION, RECONSTRUCTION

1. Introduction

Wavelet neural network is a transferring function, a kind of BP neural network topology based on the wavelet function as the hidden layer, a neural network when signal is propagated, the forward error back propagate. Wavelet neural network in the experiments use 3 layers network: input layer, hidden layer and output layer [1-3].

With Introduction into the field of neural network, prediction theories and methods of forecasting produced a qualitative leap [4]. The traditional linear prediction methods, such as Auto Regressive model, Moving Average in solving the problems of nonlinear models prediction encountered great difficulties, and neural network in nonlinear prediction has its unique advantages, it does not need to build complex nonlinear systems and mathematical model of explicit relationships, it can extracts data characteristics and internal rules through the training data samples. It makes the information distributed storage come true, resulting in associative memory. Thus the untrained samples can be extrapolated to predict the effect so that it provides a powerful tool for nonlinear prediction [5-8]. It was for the first time that carrying out forecasting by using neural network for nonlinear time series, pioneering the field of neural networks used to predict in 1987 [9-13]. After that, neural network had a rapid development in the application of prediction. Wavelet analysis, a mathematical theory developed in recent years, is considered a major breakthrough since the Fourier analysis. Based on wavelet analysis, Wavelet network is a class of network to be constructed that combines time-frequency localization properties of wavelet transformation and self-learning ability of neural network [14-17]. Wavelet neural network has received growing concern as a novel neural network. It is both possessed of time-frequency localization properties of wavelet and neural network's function approximation and generalization ability. And it has wined a strong advantage in the field of predicting [18].Currently, as for the neural network to predict, there are two main forms: Trend forecasting and regression-based causality, corresponding time series prediction and multiple regression prediction. Neural networks, with distributed, associative, memorial and strong generalization ability, as well as self-learning ability and fault tolerance, can approximately approach nonlinear functions with arbitrary precision [19-20]. It can not be matched by the linear prediction method. For most predictive objects, especially data with non-linear relationship, using the neural network will get higher prediction accuracy. However, there are the following problems to come forth when the neural network is used to predict: randomness of predicting results, lack of transparency in mechanism, difficulty to determine the initial parameters, the phenomenon of over-fitting and easiness to fall into local minima and so on. Most of those problems need to be determined that based on the experimental results, by using statistical methods to evaluate the predicted results, or using trial and error to find the optimal parameter that is convenient for further prediction.

The more prominent problem of above-mentioned problems is the randomness of neural network's forecasting result, wavelet neural network has no exception, that is, many predicted results are different, sometimes dispersive, namely the prediction accuracy of neural networks has uncontrollable nature. In this regard, there is little introduction in the current literature. This paper presents a simple and practical predicting method for wavelet neural networks, and can get a stable prediction results.

This paper mainly made a work in the following areas expansively and innovatively:

(a)As for randomness of neural network model in predicting the presence, lack of transparency in mechanism, difficulty to determine the initial parameters, the phenomenon of over-fitting and easiness to fall into local minima, this paper presents a compacted model of wavelet neural network. The model is a simple and practical method for determining the prediction, which transplant the wavelet function to hidden layer of neural network in place of Sigmoid activation function, using a command in randomly determined state to obtain certain predictions. And compared with the wavelet neural network of programming and BP network, this method is suitable for large quantities of data's training of art economic, has its adaptability of data sample and ability of robustness, especially for time series with high frequency and randomness having a better ability to adapt, with features of identifying predicted results and practicability. And it can significantly improve training's speed, prediction accuracy and prediction efficiency of the model.

(b) In order to further validate the correctness and validity of the proposed compacted model of wavelet neural network for art economic, a experiment of Beijing and Guangzhou was carried on in the environment of MATLAB R2006b which wad based on wavelet packet transformation and wavelet neural network's art economic difference. Network structure is 7-15-1; training precision is set to 0.0001; function of hidden layer is wavelet network toolbox "$wavenet\_tool$"; the output layer selects "$purelin$" function; it was trained by using the "$trainlm$" algorithm. The initial condition in the experiment is set to Q = 9, which uses the command rand ('state', 9) initialized wavelet network parameters. The simulation results show that: the compacted model of wavelet neural network has the characteristics of strong robustness, high speed of training, easy operation.

2. Problem Model

A large number of experiments of neural network's prediction model show that: the initial parameters of the network have a great influence on the predicted results of art economic . When the network structure is determined, namely the number of neurons of the network's input layer, hidden layer and output layer, and the learning rate, training accuracy are determined, the predicted results depend on initial parameters of the network. The initial parameters include network weights and threshold limit values and as for wavelet neural network it also comprises translation factor and scale parameters.

The initial parameters of neural networks are usually set as random number [-1, 1], and it is the leading cause of predictions' uncertainty. In the premise of determining the network structure, if the initial parameter set a determined value, predictions must be unique. Experiments show that as to the commonly used three-layer neural network, the initial value of network parameters has the greatest impact, followed by training's accuracy, the number of hidden layer's neurons, learning rate and momentum factor and so on.

Whether it is for BP network or for wavelet neural network, the network's initialization process is very important for whether the network's subsequent study is converged or not and for the speed of convergence; initial weights are well chosen, they can greatly accelerate convergence; initial weights are set incorrectly, then the times of learning will be greatly increased, even contributing to non-convergence; as for wavelet network, if the scale parameter and the initialization of displacement parameter are inappropriate, it will cause the learning process of the entire network does not converge.

Chen Guo had proposed several initialization methods of network parameters, which revealed the links among initial parameters, network structure and learning samples along with some limitations [21]. Currently the methods to optimize the network initial parameters such as genetic algorithms, particle swarm optimization, chaos optimization and so on, are very impressive for more complex networks. Furthermore, optimization algorithm itself is not just one time to determine the optimal values.

3. Proposed Method

3.1. Compacted WNN

Compacted wavelet neural network is a product of combination between wavelet function and neural network, referring to a wavelet function or scaling function as activation function of neural network's hidden layer forming neurons, like Morlet wavelet function in place of BP neural network's hidden layer, Sigmoid activation function, the structure of the network is shown in Figure 1.

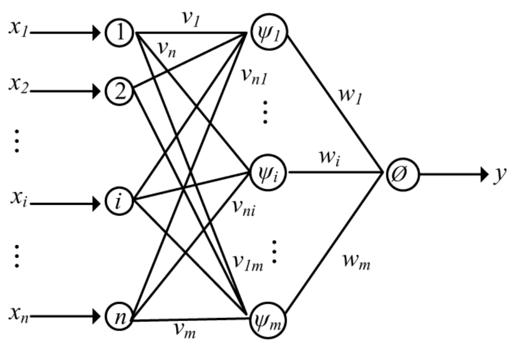

Figure 1. Wavelet neural network's structure

Figure 1 shows the three layers structure of wavelet network. Wherein, xi is the network's input variable, outputting to be a neuron. In this paper the outputting y corresponds to art economic difference; $\psi_i(t)$ is the wavelet function ($i=1,2,...,m$); v_{ni}, w_i are connection weights between input layer / hidden layer, hidden layer / output layers. The currently used mother wavelets have good locality and smoothness like spline wavelet and Morlet wavelet. These functions' flexibility and parallelism can constitute an orthogonal basis of L2 (R), generating the most precise wavelet series at approximation. The hidden layer in this paper adopts Morlet wavelet function, the expression is described as

$$\psi(x) = \cos(1.86x)\exp\left(-x^2/2\right) \quad (1)$$

Wavelet transformation corresponds to the Hilbert space of square integral L2 (R), if there exists a function

$$\psi(x) \in k^2(t), \int_t |\psi(k)|^2 \, dt \prec +\infty$$

And its Fourier transforms into

$$g_\psi = \int_t \frac{|\psi(\mu)|^2}{|\mu|} j\mu \prec +\infty \quad (2)$$

The function ψ (t) is a based wavelet, through the based wavelet's flexibility and parallelism, it can obtain a bases wavelet's function family

$$\psi_{a,b}(k) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{k-b}{a}\right) \quad (3)$$

Wherein: a, b, R, a≠0. a and b are factors of flexibility and parallelism. Wavelet transforms into

$$\begin{aligned}(\varpi_\mu t)(a,b) &= \langle t(k), \psi_{a,b}(k)\rangle \\ &= \int_\mu f(k)\psi^*_{a,b}(k)\,dt\end{aligned} \quad (4)$$

Ψ (x) is the wavelet function. Formula (4) shows the change of wavelet is similar to the projection of the signal wavelet function on the based wavelet function, or a comparison between the signal and the wavelet in the associated position of a, b to transform into ($w\psi f$) (a, b), which described the degree of similarity in two aspects. The size of the projection reflects of the size of signal on the scale energy.

In Figure 1, the wavelet network structure consists of three layers: the input layer, hidden layer and output layer. Let three neurons, set as $n,m,1$ respectively, excitation function of each hidden layer's neuron is $\psi a,b(x)$, the excitation function of output layer neuron takes Sigmoid, then the output expression is

$$t^e(k) = \phi\left(\sum_{k=1}^{n} w_n \psi\left(\sum_{j=1}^{m} h_{ik} s_i^j\right)(k) - l_i)/g_i\right) \quad (5)$$

Wherein, $p=1,2,...,m$, p = 1, 2, ..., P (P is the number of samples). Let y be the actual value, $\hat{t}$ the predicted value, then the training samples p, taking the error energy function:

$$L = \frac{1}{2}\sum_{j=1}^{p}\sum_{i=1}^{m}\left(\hat{t}_i^j - t_i^j\right)^2 \quad (6)$$

$$J_{ik}(s) = j_{ik}(s-1) - \eta_\mu \frac{\partial s}{\partial s_{ik}} + \partial\Delta s_{ik} \quad (7)$$

$$r_i(s) = r_i(s-1) - \eta_\varpi \frac{\partial s}{\partial r_i} + \partial\Delta r_i \quad (8)$$

$$a(s)=a(s-1)-\eta_a \frac{\partial r}{\partial a}+\partial \Delta a \quad (9)$$

$$b(s)=b(s-1)-\eta_b \frac{\partial r}{\partial b}+\partial \Delta b \quad (10)$$

Wherein: $\eta_\mu, \eta_\varpi, \eta_a, \eta_b$ are the learning rates, α is the momentum factor, by adjusting the parameters of WNN, make the formula (6) minimize.

3.1.2. Wavelet Neural Network Toolbox

The new version of MATLAB software offers Wavelet networks order to achieve wavelet neural network, but it is far from easiness to use BP neural network toolbox. Currently the application of wavelet neural networks in art economic is mainly achieved by programming. The general program designation is more complex, the programming cycle is long, and their types are different, especially for certain data sets or large quantities of data which are not easy to train, so such that the inherent superiority of wavelet neural network has been confined. The key to achieve the wavelet neural network toolbox is a user-defined transferring function, that is, there is a need to create wavelet function. By replacing BP neural network toolbox $\tan sig, \log sig$ with Morlet wavelet function and its derivatives:

$$v=\cos(1.78x)\times\exp\left(-x^2/2\right) \quad (11)$$

$$\frac{sy}{sx}=-x\cos(1.78x)\times\exp\left(-x^2/2\right) \\ -1.78\sin(1.78x)\times\exp\left(-x^2/2\right) \quad (12)$$

Above treatments were replaced only for activation functions, not having a function of flexibility and parallelism. The network is lack of a flexible factor and paralleled factor b. the following evidence, which can be later incorporated into the equivalent connection weights and threshold limit values.

$$\psi_{a,b}\left(\sum_{i=1}^{m} v_{ik}x_i^p+\theta_{ik}\right)=\psi\left(\left(\sum_{i=1}^{m} v_{ik}x_i^p+\theta_{ik}-r_h\right)/a_k\right) \\ =\psi\left(\sum_{i=1}^{m}\frac{t_{ik}}{a_k}s_i+\frac{\theta_{ik}-s_k}{a_k}\right)=\psi\left(\sum_{i=1}^{r}\mu' s_i+\theta_{ik}^{'}\right) \quad (13)$$

From the formula (13), it shows that the flexible factor ah and the paralleled factor b_h in the formula (5) shift into factors and threshold limit values, which weights and threshold limit values include function of flexible and paralleled factors. Training neural network like ordinary BP neural network's, provides training functions by using the toolbox, such as training function taking "*trainlm*", the activation function of output layer neuron using "$\log sig$" or "*purelin*".

3.1.3. Initialization Method of neural network parameters

There is the problem when using wavelet toolbox in experiments: Wavelet networks toolbox results is slightly better than BP neural network toolbox from a overall point of view in art economic. As predicted results of for art economic are random numbers, their results are equal in a number of forecasting process. From this perspective, the toolbox is of little significance, and it fails to reflect the superiority of wavelet neural network. Therefore, this article uses the command rand ($state, Q$) to obtain stable predictions, where Q is a self-defined parameter, which means network forecasting performance. The value of Q is to be determined by experiments, the command can reproduce a random number once produced, preferably by changing the initial Q value to get a better parameter. The evaluation of Q's value adopts average absolute percentage of forecasting errors. In the paper, Q is defined as the control parameters of the neural network prediction accuracy.

In MATLAB software, the function of command rand ($state, Q$) is: reset generator to its original state, which means the state of generating random number. The effect is that: because of the difference of random number generated in each rand, in order to obtain the same state as the previous, it implements this function to generate the same random number.

Sequence of numbers generated by the rand command is decided by the inner generator of MATLAB. Generator, set to the same fixed state (Q), helps accomplish repetitive calculation; Q, set to be at different states, gets different results. It is the only calculation result that is the value of their application. However, no improvement of its statistical properties is made. As MATLAB restarted, at a fixed Q, rand generated the same sequence of numbers. Expressions and meanings are as follows:

Rand ('state', 0): reset the generator in the initial state;

Rand ('state', S): reset generator to S of its resolution states;

Rand ('state', J): reset generator to J of its first states for integer J

Experiments is carried out under the instruction of rand ('state', Q) which can predict the network's repeatability, comparison among different networks under the same conditions; and this prediction is very important.

Experiments is carried out by taking art economic difference data with poor regularity as the object of the research. In order to extract geological features of art economic difference data, the study decomposes the original sequence through using wavelet packet's transformation, uses different wavelet neural networks of art economic to predict in sub-sequences, and then receives final prediction results for each sub-sequence prediction results obtained by wavelet packet reconstruction.

Art economic difference is a very complex geological parameter. It is affected by many factors, such as geological structure, coal seam thickness, coal structure, depth of burial and other natural factors, as well as other related mining technology. These factors themselves are random variables; they have mutual restraints among various factors and reinforce each other. Therefore, the art economic difference rate is actually a multi-variable, time-varying, gray, highly nonlinear and complex dynamic system. It is often difficult to accurately predict. The size of Methane Emission not only reflects the degree of risk of different coal seams, but also becomes an important indicator of the level of safety technology which decides to develop a new well, the new mining area, the new face size, ventilation.

At present, the prediction of art economic difference in BP network is more common, but the presence of BP neural network has the problems of long time convergence, easiness to fall into local minima.

3.1.4. Wavelet Packet's Transformation Theory

Wavelet Packet's Transformation

Let $\{ s_j; j \in z \}$ (Z is the set of integers) constitutes L2 (R) (R is a real number) on the orthogonal multi-resolutive analysis, its scaling function, the mother wavelet function are φ (t) and ψ (t) respectively. They satisfy the following two-scale equation.

$$\begin{cases} \varphi(s) = \sqrt{2}\sum\limits_{j\in z} l(k)\varphi(2s-k) \\ \psi(s) = \sqrt{2}\sum\limits_{j\in z} f(k)\varphi(2s-k) \end{cases} \tag{14}$$

Wherein: coefficients h (k) and g (k) is the filter coefficients of a multi-resolutive analysis; $l(k) = -1_{ik}(1-k)$, that is, two coefficients have an orthogonal relationship.

The scale space v_j and wavelet subspace y_j are described as a new space μ_j^n. Namely, $\mu_j^0 = v_j, \mu_j^1 = y_j, j \in z$, then the orthogonal decomposition in the Hilbert space $v_j + 1 = v_j \oplus y_j$ can be denoted by μ_j^n.

$$\mu_{j+1}^0 = \mu_j^0 \oplus \mu_j^1$$

Define a subspace μ_j^n as the closed space of function $s_n(t)$, μ_j^{2n} is the closure space of function $s_{2n}(t)$.

For the case of the fixed scale, define recursive function:

$$\begin{cases} s_{2n}(t) = \sqrt{2}\sum\limits_{j\in z} k(s)\omega_n(2t-h) \\ s_{2n+1}(t) = \sqrt{2}\sum\limits_{j\in z} r(s)\varpi_n(2t-h) \end{cases} \tag{15}$$

Wherein $n = 0,1,2,...,n$. When n = 0, the

$$\begin{cases} \mu_0(s) = \sqrt{2\sum\limits_{j\in z} l(k)\mu_0(2s-k)} \\ \mu_1(s) = \sqrt{2\sum\limits_{j\in z} p(k)\mu_0(2s-k)} \end{cases} \tag{16}$$

Wavelet Packet's Decomposition and Reconstruction

Let (s) ∈ (t), g_j^n can be expressed as:

$$g_j^n(s) = \sum_i tj - n_i^{j-n}\mu\left(2^j t - p\right)$$

Wavelet packet decomposition algorithm

Seeking by $g_1^{j+1,n}$ to find $\{g_1^{j,2n}, g_1^{j,2n+1}\}$

$$\begin{cases} f_i^{j,2n} = \sum\limits_k a_{k-1i} f_k^{j+1,n} \\ f_i^{j,2n+1} = \sum\limits_k b_{k-2i} f_k^{j+1,n} \end{cases} \tag{17}$$

Wavelet packet reconstruction algorithm:

Seeking by $g_i^{j,2n}, g_i^{j,2n+1}$ to find $g_i^{j+1,n}\}$

$$\begin{cases} f_i^{j,2n} = \sum\limits_k a_{k-2i} f_k^{j+1,n} \\ f_i^{j,2n+1} = \sum\limits_k b_{k-2i} f_k^{j+1,n} \end{cases} \tag{18}$$

Wavelet Packet's Analysis of Art economic difference Data

Using wavelet packet transformation to predict art economic difference data series, it is the first step to decompose wavelet packet. The selection of decomposition level may be based on the minimum prediction error. The paper selects three layers. Use the small wavelet d_{b4} to decompose 8 frequency components from low to high, as shown in figure 2.

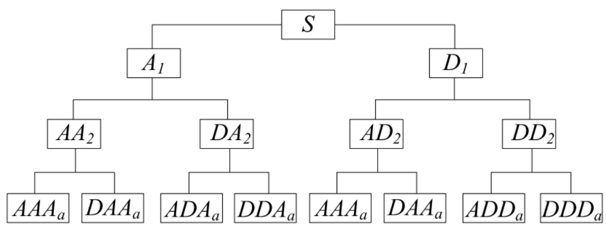

Figure 2. Wavelet packet's decomposition of three layers

In Figure 2, A represents a low frequency, D represents a high frequency, and the subscript indicates the number of layers of wavelet packet decomposition. It is can be seen that the wavelet packet's change not only further decomposition for each lower frequency section, but also further decomposition for the same high-frequency part.

Original sequence S can be expressed as:

$$s = AAA_3 + DAA_3 + ADA_3 + DDA_3 + AAD_3 + DAD_3 + ADD_3 + DDD_3 \tag{19}$$

Original experimental data is: 429 day record data of Art economic difference. Original data is the signal S, using db_4 to transform wavelet packet for getting $s30, s31, ..., s37$ of 8 sub-sequences.

Wavelet Packet-wavelet neural network prediction model

Configuration method of prediction model: original data sequence of art economic difference, the wavelet packet can be decomposed to $s30, s31, ..., s37$. Each sub-sequences using different wavelet neural network toolboxes to predict which adopts $WNN1, WNN2, ..., WNN8$. The respective predictions wavelet packet will be reconstructed to get the final prediction.

Currently there are many literature using wavelet packet analysis for fault diagnosis, but rarely used for prediction, mainly due to wavelet packet sequences, especially for high-frequency sequences generally difficult to adapt neural networks, and large forecasting workload. If the high-frequency component is uncertain, forecasting results will be greatly affected. In this paper, using wavelet neural network to predict, it can effectively extract the characteristics of high frequency sub-sequence information through wavelet neural network toolbox, so that training speed is greatly improved, and has strong robustness. The timing sequence prediction of subspace: time series forecasting estimates future observations according to the use of the past and the present value. Let the sequence of one-dimensional {x (i)} ($i = 1, 2, ... n$) with n before neighboring m of the time values (m <n), the first $n+1$ predictive value of time ($n+1$), the future and past values of a function to determine the existence of a relation:

$$\hat{x}(n+1) = f\left[x(k+1), x(k+2), ..., x(k+m)\right]$$

Similarly, with the numerical prediction of $x(k+2), x(k+3), ... x(k+m+1)$, the corresponding values of $\hat{x}(n+2)$ in the time of $n+2$, carry on the process of recursion. If the sequence {x (i)} can be divided into h group, then can get a sample set of a neural network's training ($\hat{x}h, f_h$). According to predicting effects taking $m = 7$, namely input layer neurons of wavelet neural network is 7, the output of a neuron is 1. Hidden layer neurons is $q = 2n+1, n = 7$, n is the number of network input variable, so q = 15, that is, the network structure is V. Training error precision is set to 0.0001; normalization uses command norm; anti-normalization use norm. Such data processing method avoids data appearing 0 and 1, in order to improve the model prediction performance and input normalized data into network for training.

4. Experimental Results

As for subsequence S30, in the 429 series data, using the data before seven days to predict he eighth day, and carry on recursion. Afterwards, it constitutes 422 sample set, take the first 300 samples to train neural network, the left 122 samples for test,which is form art economic data in Beijing and Guangzhou.

WNN1's designation: commence on the experiments in the environment of MATLAB R2006b. Network structure: 7-15-1; training precision is set to 0.000 1; the wavelet network toolbox function of the network hidden layer takes "*wavenet tool*", selects output layer "*purelin*" function, uses the "*trainlm*" algorithm for training. Initial conditions in the experiments is set as Q = 9, which uses the command rand ('state', 9) to initialize wavelet network parameters. The predictions of S30 are shown in Figure 3; details can be seen in Table 1. Table 1 also gives the prediction results of S31 ~ S37 and the predicted results of BP network under the same conditions of art economic.

Similar to S30, the sub-sequences of S31 ~ S37 have the same treatment. Q value determination method: range generally from 0 ≤ Q ≤ 20 can meets the requirements, Q value, as a integer, can pass the test individually, or predict the accuracy of performance indicators for programming optimization. The forecasting results are demonstrated in Figure 4 to 10, each of FIG is the comparison between actual and predicted values.

It can be seen from the results, the sub-sequence, 0.3740%, prediction accuracy of S30, is the highest; the maximum prediction accuracy of S30 is 2.111 2%; the prediction results are reproducible. Figure 3 illustrates that the wavelet network toolbox has a strong ability for fitting with the generalization, and the remaining sequences graphics show WNN toolbox method for high frequency signal is also very strong ability to adapt, and is much better than the BP network. In S30, the present method prediction accuracy is important; it is the predominant component of signal reconstruction.

Table 1. Prediction results of wavelet packet's decomposed subsequence

Wavelet packet sequence	norm	WNN too case
S30	Prediction accuracy%	0.3742
	Maximum precision%	2.1231
	The training and prediction time	84.021
S31	Prediction accuracy%	83.0963
	Maximum precision%	2309
	The training and prediction time	1.4092
S32	Prediction accuracy%	32.053
	Maximum precision%	318.01
	The training and prediction time	1.335
S33	Prediction accuracy%	87.031
	Maximum precision%	1678.02
	The training and prediction time	1.4123
S34	Prediction accuracy%	19.386
	Maximum precision%	320.09
	The training and prediction time	1.294
S35	Prediction accuracy%	56.632
	Maximum precision%	760.432
	The training and prediction time	1.254
S36	Prediction accuracy%	45.076
	Maximum precision%	1530.87
	The training and prediction time	1.253
S37	Prediction accuracy%	95.021
	Maximum precision%	1474.04
	The training and prediction time	1.3480
reconsitution	Prediction accuracy%	3.1792

Wavelet packet sequence	BP too case	selection of Q value, accuracy set
S30	3.2321	7-15-1
	8.3201	Q=9
	1.3786	0.0001
S31	455.02	7-15-1
	25218	Q=5
	1.2871	0.0001
S32	257.03	7-15-1
	3502.01	Q=19
	1.2901	0.0001
S33	277.04	7-15-1
	4267.03	Q=26
	1.2536	0.0001
S34	415.03	7-15-1
	9258.01	Q=30
	1.467	0.0001
S35	230.032	7-15-1
	3564.021	Q=11
	1.223	0.0001
S36	469	7-15-1
	24267	Q=13
	1.478	0.0001
S37	138.02	7-15-1
	3781.01	Q=2
	1.2503	0.0001
reconsitution	15.6351	

When the sub-series are predicted, you can reconstruct wavelet packet, the results are shown in Figure 11, which is the contrast of the total predicted actual and predicted values. Final prediction accuracy is 3.1454%; the maximum prediction accuracy is -14.3672%; reconstruction time required is $0.8742s$. Overall prediction accuracy is 15.6315% after BP network's reconstruction; the maximum prediction accuracy is 40.0132%.

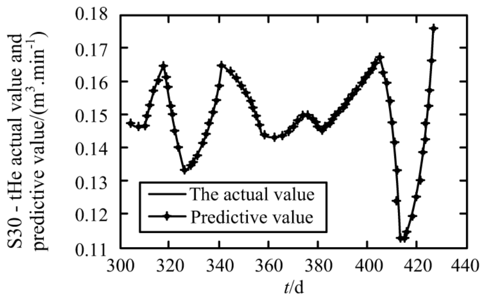

Figure 3. S30 predicting results

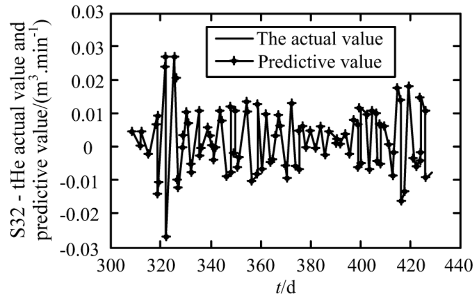

Figure 5. S32 predicting results

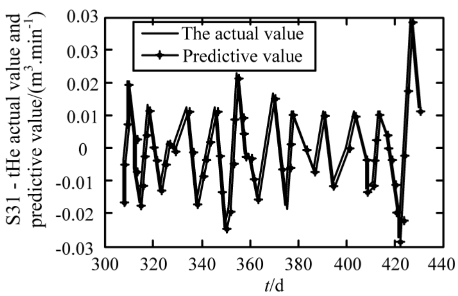

Figure 4. S31 predicting results

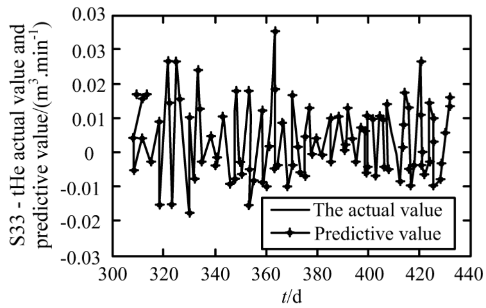

Figure 6. S33 predicting results

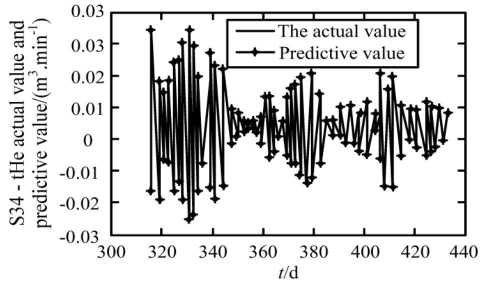

Figure 7. S34 predicting results

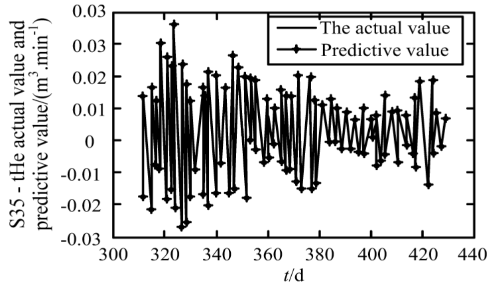

Figure 8. S35 predicting results

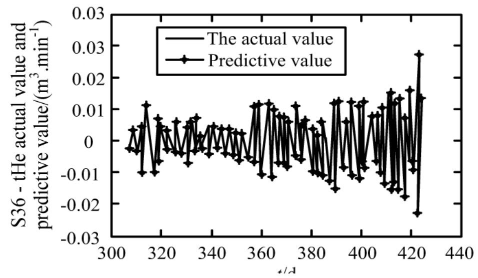

Figure 9. S36 predicting results

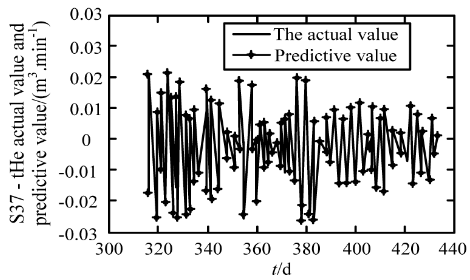

Figure 10. S37 predicting results

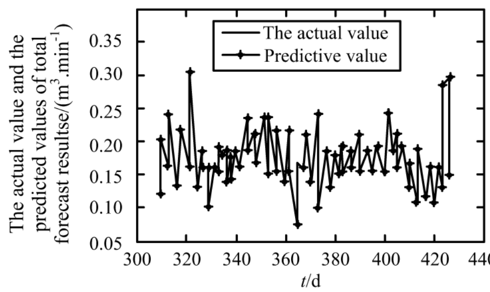

Figure 11. Predicting results after reconstruction

In the last column of Table 1, it gives the structure of the network, Q value (BP, WNN) and the setting of training prediction accuracy.

Some explanations on the Table 1 are shown below:

a) The results of the prediction accuracy in Table 1 can be repeated in experiments; the training time can not be repeated. However, its volatility is so small that its influence can be neglected.

b) BP network prediction of Table 1 is obtained under the same experimental conditions in connection with WNN , therefore the predicted result is determined. Q value is the optimal values for WNN, but it is not necessarily optimal for the BP art economic data.

c) In Table 1, it seems difficult to understand that some high-frequency sub-sequence prediction accuracy is poor. But it does not mean that overall prediction accuracy is low. The higher the accuracy is, their overall prediction accuracy can be improved.

d) Neural networks are data-driven model, a greater dependence on the data. Similarly, the prediction results of the wavelet network have a great relationship with the quality of data sample; different data may get different predictions.

Training and prediction time's calculation: training and forecasting of 8 Sub-sequence, is $10.723s$ totally; reconstructed forecasting time is 0.8731s; consuming time is $11.58734s$ totally, which does not contain operating time. It is much higher than the programmed BP's, WNN'S neural network speed, and it is sometimes difficult to train which are based on programming BP, WNN local minima due to other reasons .

It is accomplished on the experiments of S30 by using WNN1 programming prediction in art economic. Programming of WNN1 network structure: 7-15-1; learning rate: 0.3; momentum factor: 0.02. When the training accuracy is set to 0.0013 , the absolute average training accuracy is 1.5078%; the maximum precision is 6.4080%, time required for training and prediction is $12.3388s$. All sequences are difficult to train when training accuracy is set to 0.0001. When training accuracy of S31 ~ S37 is set to 0.06, it can be achieved to training accuracy requirements, but the prediction accuracy is poor, indicating that the programming of the WNN has a larger difference with wavelet network toolbox's performance.

Conclusions

Randomness is a natural characteristics of neural network's forecasting methods. Based on the research of wavelet neural network toolbox, the initialization commands of Q-value, makes random transformation of predicting models affirmative. It is an expansion of the prediction theory for wavelet neural network. Through art economic difference wavelet packet-Wavelet network forecasting examples, it shows that the method has not only both wavelet feature extraction capabilities, but also a series of advantages of BP neural network toolbox, such as higher speed of training, easier operation, applicability to large quantities of data for training and processing, data adaptability and robustness with a flexible, practical features. By controlling parameter Q to get the best predictive value, it is more convenient than optimized algorithms such as genetic algorithms, particle swarm algorithm. This method of wavelet neural network is of practical significance to promote the application of wavelet neural network in art .

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Design of RFID Security Authentication Protocol for E-Commerce Service

Xiaoli He[1], Yu Song[2], Ralf Volker Binsack[3]

1.School of Computer Science, Sichuan University of Science and Engineering, Zigong Sichuan 643000, China;
2.Department of Network Information Management Center, Sichuan University of Science and Engineering, Zigong Sichuan 643000, China
3.Winterstein 14,Niddatal,61194,Germany

Abstract
As for security of RFID network, this paper has proposed a safe, effective and scalable RFID Authentication Protocol (CRFID) with cloud database as server. Firstly, the tree-structure management tag is used to achieve privacy protection, and the time complexity of RFID system in search of cloud database is reduced from O (N) to O (logN); then, the size of each subkey in keys route of the RFID tags is increased from 4 to 60 digits to prevent tracking attacks; finally, reader determines whether the key stored in the tag is updated through the feedback message of the