RESEARCH ON THE SHORT-TERM AGRICULTURAL ELECTRIC LOAD FORECASTING OF WAVELET NEURAL NETWORK

Qian Zhang
Department of Economic Managemen ,North China Electric Power University, Baoding 071003, China, E-MAIL: hdzhq@yeah.net

Abstract: This paper proposes a new method for load forecasting—the wavelet neural network model for daily load forecasting. The neural call function is basis of nonlinear wavelets. A wavelet network is composed by the wavelet basis function. The global optimum solution is got. We overcome the intrinsic defects of a artificial neural network that its learning speed is slow, its network structure is difficult to determine rationally and it produces local minimum points. It can be seen from the example this method can improve effectively the forecast accuracy and speed. It can be applied to the daily agricultural electric load forecasting.

Key Words: Artificial Neural Network, Wavelet Neural Network, Agricultural electric Load Forecasting.

1. INTRODUCTION

A daily agricultural electric load forecasting means the load forecasting that time units are the hour, day or month. Because its tendency has a strong randomness, the determination of mathematical models is difficult. The improvement of forecasting accuracy is difficult.

At present, one of the effective forecast methods is the artificial neural network. It can express a complex nonlinear function. But then it has some intrinsic defects that its learning speed is slow, its network structure is difficult to determine rationally and it produces local minimum points.

In order to overcome these questions, we propose to forecast short-term load with the wavelet neural network. It combines a wavelet transformation with an artificial neural network. It is a new mathematical model method. First a wavelet series is got through an expansion and contraction factor and a translation factor. Then a wavelet function network is formed. Because two new parameters that are an expansion and contraction factor and a translation factor are used, the wavelet neural network has more degree of freedom than an artificial neural network (Karaki et al., 2005). Thus it has a better function approximation ability. The wavelet neural network that it is combined by the series of less term can get excellent approximation effect. The network structure is combined with wavelet basis functions; the subjective determination is avoided (C.N.Lu et al., 2003). Because its network weight number is linear and learning objective function is convex, the global optimum solution is got. Because the network structure is a single implicit layer, the learning speed is faster than general network (Niu et al., 1994).

2. THE WAVELET CONCEPT AND THE WAVELET TRANSFORM

For setting up the load forecast model of wavelet neural network, first we introduce some basic concepts of wavelet and wavelet transform.

We call the square integral function $\varphi(t) \in L2(R)$ that it is asked to satisfy the admissible condition:

$$\int_{-\infty}^{+\infty} [\hat{\varphi}(\omega)]^2 [\omega]^{-1} d\omega < +\infty \qquad (1)$$

basic wavelet or mother wavelet. $\hat{\varphi}(\omega)$ is the Fourier Transform of the $\varphi(t)$. Let

$$\varphi_{ab}(t) = \frac{1}{\sqrt{|a|}} \varphi\left(\frac{t-b}{a}\right) \qquad (2)$$

Among them, a, b are real number, and $a \neq 0$, φab is called the wavelet basis that it is generated by mother wavelet and it depends on the parameter a, b.

Let $f(t) \in L2(R)$, The f(t) is tendency function that it shows the variance law of the agricultural electric load.

Let the wavelet transform of the f(t)

$$W_f(a,b) = (f, \varphi_{ab}) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(t)\varphi(\frac{t-b}{a})dt \qquad (3)$$

Due to the specificity of the load, this transform is discussed only in the real numbers. From (3), the variance of the parameter b in the wavelet basis has the use of translation. The parameter a not only changes the frequency spectrum structure but also changes the length of its window. Thus, a, b are called respectively the expansion and contraction factor and the translation factor of φab (t). The similarity of the Fourier analysis, the wavelet analysis resolves the signal function into the wavelet normal orthogonal basis. It constructs a series to approximate the signal function. This linear combination has an optimum recognition capacity (Srinivasan et al., 2005) .

The mother wavelet is asked to satisfy condition (1), Thus we get

$$\int |\varphi(t)|^2 dt < \infty \qquad (4)$$

The condition (1) determines the locality behavior of the wavelet. It equals 0 without a limited interval or approximates 0 fast. The formula (4) determines that the wavelet has the limited energy and is an oscillation (the positive number part equals the negative number part). The wavelet's name is produced from here.

The mother wavelets with the better locality property and smooth property have the spline wavelet and Morlet wavelet usually. Its system of the expansion and contraction and translation composes the normal orthogonal basis of L2(R). The wavelet series generated can approximate f(t) optimally (Rutkowskil et al., 2004).

The similarity of the Fourier transform, the wavelet transform has also a inversion formula.

$$f(t) = \frac{1}{C_\varphi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} W_f(a,b)\varphi_{ab}(t) \frac{dadb}{a^2} \qquad (5)$$

Among them,

$$C_\varphi = \int_{-\infty}^{+\infty} |\varphi(\omega)|^2 |\omega|^{-1} d\omega \qquad (6)$$

3. THE LOAD FORECASTING MODEL OF THE WAVELET NEURAL NETWORK

In the wavelet neural network, we replaces the nonlinear sigmoid function with the nonlinear wavelet basis. The fitting of a load historical sequence is completed with the linear superposition of the nonlinear wavelet basis. The limited terms of a wavelet series can approximate the load historical curve. The load curve can be fitted with the wavelet basis φab(t)

$$\hat{y}(t) = \sum_{k=1}^{L} \omega_k \varphi(\frac{t-b_k}{a_k}) \qquad (7)$$

$$\hat{y}(t) = \sum_{k=1}^{L} \omega_k \varphi(\frac{t-b_k}{a_k}) \qquad (7)$$

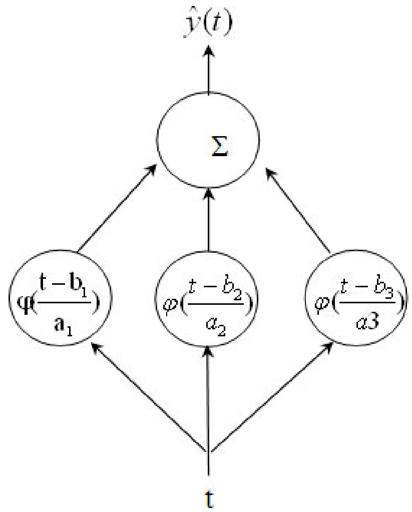

Figure 1. the wavelet neural network structure

In (7), $\hat{y}$ (t) shows the forecast values sequence of load curve y(t). ωk are weight numbers. bk are translation factors. ak are expansion and contraction factors. L is wavelet basis number. In Figure1, we give the structure of the wavelet neural network. (see Figure 1)The network is a single implicit layer. It only contains an importation node and a exportation node. We need to determine the network parameters ωk ak bk and L. Let the sequence y(t) and sequence $\hat{y}(t)$ are fitted optimally. The parameter ωk ak and bk can be optimized on the basis of the minimum square error energy function E_L.

$$E_L = \frac{1}{2}\sum_{t=1}^{L}\left[y(t) - \hat{y}(t)\right]^2 \tag{8}$$

We determine L with the method of stepwise test, Thus the network structure is determined also. to determined every L, we .compute optimal parameters ωk ak and bk by(8) as follows.

First, we use Morlet mother wavelet in(7)

$$\varphi(t) = \cos(1.75t)\exp(-\frac{t^2}{2}) \tag{9}$$

Let $T = \frac{t - b_k}{a_k}$, then the gradient of (8) is showed respectively as follows.

$$g(\omega_k) = \frac{\partial E}{\partial \omega_k} = -\sum_{t=1}^{L}\left[y(t) - \hat{y}(t)\right]$$

$$\cos(1.75T)\exp(-\frac{T^2}{2})$$

$$g(b_k) = \frac{\partial E}{\partial b_k} = -\sum_{t=1}^{L}\left[y(t) - \hat{y}(t)\right]\omega_k$$

$$[1.75\sin(1.75T)\exp(-\frac{T^2}{2})$$

$$+\cos(1.75T)\exp(-\frac{T^2}{2}T)]/a_k$$

$$g(a_k) = \frac{\partial E}{\partial a_k} = -\sum_{t=1}^{L}\left[y(t) - \hat{y}(t)\right]\omega_k$$

$$[1.75\sin(1.75T)\exp(-\frac{T^2}{2})T$$

$$+\cos(1.75T)\exp(-\frac{T^2}{2})T]/a_k = Tg(b_k)$$

Network parameters ωk bk and ak are optimized with the conjugate gradient method. Let vector ω=(ω1, ω2,…ωk…ωL)) , g(ω)=(g(ω1),g(ω2)…g(ωk)…g(ωL)). S(ω)i shows the ith cyclic search direction of the function of w. Then

$$S(\omega)^{i} = \begin{cases} -g(\omega)^{i} & i = 1 \\ -g(\omega)^{i} + \\ \dfrac{g(\omega)^{iL} g(\omega)^{i}}{g(\omega)^{(i-1)L} g(\omega)^{i-1}} \cdot s(\omega)^{i-1} & i \neq 1 \end{cases}$$

The weight vector is regulated as follows.

$$\omega^{i+1} = \omega^{i} + \alpha_{w}^{i} S(\omega)^{i} \qquad (10)$$

4. THE APPLIED STUDY OF SHORT-TERM DAILY LOAD FORECASTING IN CHINA LIAONING POWER

Applying the new method put forward in the paper, we study the daily load forecasting in Liaoning Power Network. The selected forecasting data is the history data and weather factors in October 2006.The agricultural electric load of 24 o'clock of October, 20, 2006 is to be forecasted. To compare the two models, forecast methods are elected by wavelet neural network model (WNNM) and artificial neural network model (ANNM) respectively. Through the imitation computation, we know that the accuracy and speed of the WNNM are raised obviously. (see Figure 2, 3, 4)

Table 1. The new method forecasting analysis of the load in China Liao-ning power system.

Time	Actual load	ANN Forecasting	ANN Relative error%	WANN Forecasting	WANN Relative error%
1	841.40	854.53	1.56	851.84	1.24
2	835.37	846.06	1.28	845.31	1.19
3	823.13	814.40	-1.06	816.71	-0.78
4	830.54	820.41	-1.22	824.81	-0.69
5	845.34	837.06	-0.98	837.56	-0.92
6	856.02	849.43	-0.77	847.55	-0.99
7	888.97	898.22	1.04	894.13	0.58
8	864.13	880.64	1.91	873.38	1.07
9	907.97	891.35	-1.83	895.80	-1.34
10	968.16	988.59	2.11	985.10	1.75
11	985.78	1005.98	2.05	1002.14	1.66
12	953.11	939.10	-1.47	938.62	-1.52

13	950.53	963.65	1.38	960.23	1.02
14	971.63	962.98	-0.89	965.12	-0.67
15	977.39	968.01	-0.96	969.76	-0.78
16	1002.71	1017.05	1.43	1009.43	0.67
17	1043.51	1055.93	1.19	1053.32	0.94
18	1078.58	1096.60	1.67	1087.97	0.87
19	1077.64	1090.24	1.17	1088.84	1.04
20	1025.51	1046.12	2.01	1039.35	1.35
21	1016.83	1036.86	1.97	1033.81	1.67
22	1009.01	993.37	-1.55	991.35	-1.75
23	971.72	954.62	-1.76	959.48	-1.26
24	908.24	898.80	-1.04	901.34	-0.76

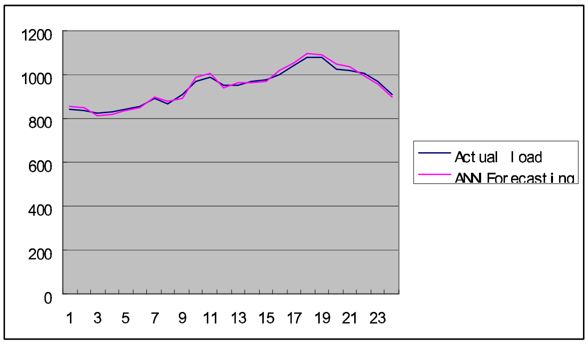

Figure 2. The ANN analysis of the load in China Liaoning power system

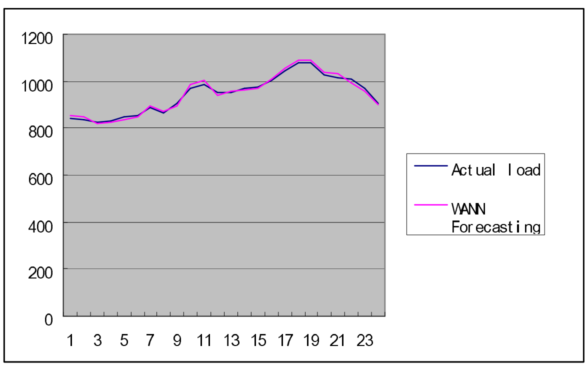

Figure 3. The WANN analysis of the load in China Liaoning power system

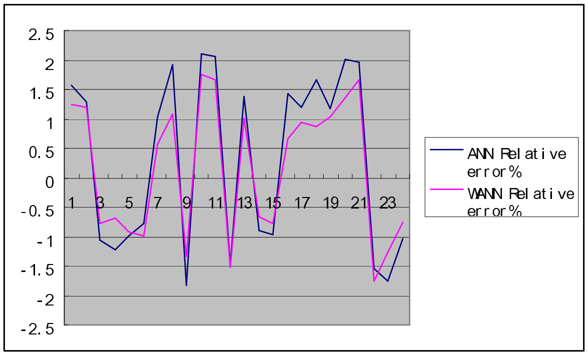

Figure 4. Relative error analysis of the load in China Liaoning power system

5. CONCLUSIONS

(1) In this paper, we propose the wavelet neural network forecast model of agricultural electric load. It overcomes the intrinsic defects of an artificial neural network that its learning speed is slow, its network structure is difficult to determine rationally and it produces local minimum points.

(2) Its nervous cell function is basis of nonlinear wavelets. We get the global optimum fitting effect. Then the accuracy is improved. The network structure is determined rationally with the stepwise test method, Because the network is a single implicit layer structure, Its speed is improved obviously It can be used to forecast daily agricultural electric load.

(3) Through the imitation computation, we prove that the accuracy and speed are improved obviously. This is a new and effective method of agricultural electric load forecasting.

ACKNOWLEDGMENTS

This paper is supported by North China Electric Power University Youth Scientific Research Fund.（200611039）.

REFERENCES

Niu Dongxiao,: Adjustment Gray Load Forecasting Model of Power System. The Journal of Gray System, 1994,6(2): 127-134

Karaki S.H.: Weather Sensitive Short-term Load Forecasting Using Artificial Neural Networks and Time Series. International Journal of Power and Energy Systems,2005,l9(3):25 1-256

XieHong, ChengZhiye, NiuDong xiao: The Research of Daily Load Forecasting Model Based on Wavelet Decomposing and Climatic Influence. Proceedings of the Csee,2004,21(5):5-10

Srinivasan D.,Chang C.S., Liew A.C.: Demand Forecasting Using Fuzzy Neural Computation, with Special Emphasis on Weekend and Public Holiday Forecasting. IEEE Transactions on Power Sys-tems,2005,10(4):1897-1903

Rutkowskil L: Generalized Regression Neural Network in Time Varying Environment. IEEE Transaction on Neural Network,2004,15(3):576-596

Tomandl D., Schober A．: A Modified General Regression Neural Network with New, Efficient Training Algorithms as a Robust Black Box Tool for Data Analysis．Neural Networks，2001,14(8):1023-1034

He S. D., Qu T., Huang X. H.: An Improved Neural Network Method for Short Term Load Fore-casting. Automation of Electric Power System,2000,21(11):13-14

Charytoniuk W.,Chen M. H.: Very Short-term Load Forecasting Using Artificial Networks. IEEE Trans. on PWS, 2000.15(1):263-268

T. Haida and S. Muto, “Regression based peak load forecasting using a transformation technique,” IEEE Trans. Power Syst., vol. 9, pp.1788–1794, Nov. 1999.

S. Rahman and O. Hazim, “A generalized knowledge-based short term load-forecasting tech-nique,” IEEE Trans. Power Syst., vol. 8, pp. 508–514, May 1998.

S. Rahman and G. Shrestha, “A priory vector based technique for load forecasting,” IEEE Trans. Power Syst., vol. 6, pp. 1459–1464, Nov.2003.

T. Senjyu, S. Higa, T.Yue-Jin, and K. Uezato, “Future load curve shaping based on similarity using Fuzzy logic approach,” in Proc. Int. Power Eng. Conf (IPEC), vol. II, 2004, pp. 483–488.

C. N. Lu and S. Vemuri, “Neural network based short term load forecasting,” IEEE Trans. Power Syst., vol. 8, pp. 336–342, Feb. 2003

R. Lamedica, A. Prudenzi, M. Sforna, M. Caciotta, and V. O. Cencellli, “A neural network based technique for short-term forecasting of anomalous load periods,” IEEE Trans. Power Syst., pp. 1749–1756, Nov. 1996.

S. AlFuhaid, M. A. El-Sayed, and M. S. Mahmoud, “Cascaded artificial neural networks for short-term load forecasting,” IEEE Trans. Power Syst., vol. 12, pp. 1524–1529, Nov. 1997.

D. Papalexopoulos and T. C. Hesterberg, “A regression-based approach to short-term load forecasting,” IEEE Trans. on Power Syst. vol. 5, no. 4, pp. 1535-1550, 1990.

H. S. Hippert, C. E. Pedreira, and R. C. Souza, “Neural networks for short-term load forecasting: A review and evaluation,” IEEE Trans. On Power Syst., vol. 16, no. 1, pp. 44-55, 2001.