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Fuzzy Wavelet Neural Networks for City Electric Energy Consumption Forecasting

Ping Zhang[a],Hui Wang[b]

[a]Henan Institute of Engineering,Zhengzhou 451191，China，xxxwsy@gmail.com
[b]Zhengzhou College of Animal Husbandry Engineering,Zhengzhou, Henan Province, China

Abstract

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 presents a fuzzy wavelet neural network (FWNN) approach for annual electricity consumption in high energy consumption city. It is claimed that, due to high fluctuations of energy consumption in high energy consumption cities, conventional regression models do not forecast energy consumption correctly and precisely. Although ANNs have been typically used to forecast short term consumptions, this paper shows that it is a more precise approach to forecast annual electricity consumption. Furthermore, the FWNN approach based on ANN is used to show it can estimate the annual consumption with less error.
Actual data from high energy consuming (intensive) from 1983 to 2003 is used to illustrate the applicability of the FWNN approach. This is the first study to present an algorithm based on the ANN and wavelet for forecasting long term electricity consumption in high energy consuming city. The prediction effect of wavelet neural network prediction model is proved in matlab7.0 simulation environment. A better prediction result is gained, and the defect of falling into local hypo-strongpoint is overcome, at the same time, the rate of training is raised compared with the prediction model based on artificial neural network. The calculation result shows that the presented model is effective.

Keywords:electric energy consumptin; nonlinear sequence; fuzzy wavelet neural networks; forecasting

1.Introduction

Over the last decade the electric energy consumption in the residential sector has significantly increased especially in the summer season, because of the increasing use of airconditioning(AC) systems, that has drastically changed the thermal comfort needs of urban population in the developed countries. The strong penetration of the AC equipments on the market was also quickened by the sudden and rapid reduction of their cost along with the significant temperature rise in densely built urban areas with respect to the surrounding areas, known as ‘urban heat island’ effect [1]. The particular microclimatic conditions of the urban areas have in fact a significant influence on the thermal balance of the buildings.

A good demand forecasting is the essential prerequisite of an energy system study for not only aiming at costefficient investments in the capacity expansion planning, but also plays an effective role in monitoring environmental issues as well as setting tariffs and relevant plans for demand side management studies. As a result of these, energy demand forecasting studies constitutes the vital part of energy policy of countries, especially for those countries whose energy demand is

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growing relatively quickly, as the case of China. With its developing economic structure, its demand for energy, especially for electricity, is growing relatively quickly as a result of the growth in its economy in the recent years. Gross electricity consumption was 24940.8 100 million kwh in 2005, and 28588.4 100 million kwh. According to the projections, that is still on the increase in the following years. This situation shows that electricity sector in China is in a dynamic change. Therefore, this kind of structure of energy demand in city requires a detailed effort for an accurate prediction. In literature, considerable efforts have been made for energy demand forecasting.

The avarage annual consumption of electricity of household is 2825 100 million kwh, and 3252 100 million kwh in 2006. With the increasing development of economics and the promotion of living, it causes the usage of electricity for industry and people's livelihood to increase sharply. As a result, the supply and demand issue of electricity becomes problematic in the height of summer. Since the storage of electricity is not easy, the efficient monitoring and control of the electricity demand, is one way of increasing the nimbleness of electricity allotment. A demand-control system for electric power is a possible solution to this issue. It has drawn a lot of attention from government, enterprises and researchers to solve the troublesome issue of electricity. The electric demand-control system may also help cut down on the electricity bills and avoid penalties as well.

Since the 1960s, numerous researchers have studied the electric consumption forecasting. They developed various models to nvestigate the prediction of electric energy consumption, such as time-series, regression analysis and artificial intelligence [2-5].The time-series method assumes that the historical data of focused system is steady. In this method, random statistic analysis methodology was adopted to determine the prediction. The defect of this method is that it needs a great amount of historical data with good statistic distribution to get accurate forecasting. Differently, by using regression analysis, one is able to establish model and parameters using a little data. However, the accuracy of prediction is not good enough, because the adopted linear model is too simple. Likewise, the artificial intelligence approach, such as expert system or Neural Network, needs a lot of prediction rule and practical experience from specific experts in this field. Different experts may have different results, and it also needs large historical data banks to get accurate forecasting.

In this paper, we present a fuzzy wavelet neural electric energy consumption predictor. The advantages of the proposed improved artificial neural network consumption predictor are its fast calculation and ease of implementation with a few data inputs required. Because FWN combines the time-frequency localization ability of wavelet, fuzzy inferring and the education character of ANN together, its ability to reach the global best results is greatly improved. The FWN includes a set of fuzzy rules and several sub-WNNs. Every sub-WNN, corresponding to a certain fuzzy rule, consists of wavelets with a specified dilation. By adjusting the translation parameters of the wavelets and the shape of membership functions, the accuracy and generalization capability of FWN can be remarkably improved.

2.Wavelet neural network model and algorithm

2.1.Wavelet network and its characteristics

Wavelet, or small region wave, usually refers square enterable function $\psi(t)$, or $\psi(t)\in L2(R)$, and its Fourier transformation $\Psi(\omega)$ meets: $\int_R \frac{|\Psi(\omega)|^2}{\omega} d\omega < \infty$, $\psi(t)$ is called a base wavelet (or wavelet mother function). Wavelet mother function has compactly supported or approximate compactly supported, and has the character of plus-minus alternating[3].

Let the wavelet mother function $\psi(t)$ extend and shift, and given the extension factor(or scale factor) is a, shift factor is τ ,then the function is:

$$\psi_{a,\tau}(t) = a^{-\frac{1}{2}}\psi\left(\frac{t-\tau}{a}\right) \tag{1}$$

where $a>0$, $\tau \in R$ called $\psi_{a,\tau}(t)$ wavelet base function depending a and τ. Because scale factor and shift factor are continuous variation, $\psi_{a,\tau}(t)$ is called continuous wavelet base function. They are a set of functions originated from the same mother function after extending and shifting. Because wavelet mother function has compactly supported or approximate compactly supported. The wavelet base function after shifting and extending have the character of time-frequency locality [6]. This is the starting point that we presents fuzzy wavelet neural network.

In order to study the time-domain and frequency-domain characteristics of information under local scope, WT is usually adopted to analyze the information. Under the wavelet base, any function f(t) ∈L2（R）is expanded as :

$$WT_f(a,\tau) = \langle f(t), \psi_{a,\tau}(t) \rangle = \frac{1}{\sqrt{a}} \int_R f(t) \overline{\psi(\frac{t-\tau}{a})} dt \tag{2}$$

The expansion is called continuous wavelet transformation (CWT).

2.2.Structure of fuzzy wavelet neural network

Wavelet network is a new type feed forward network based on wavelet analysis. It is a new type function connection nerve network treated wavelet function as base. The expression of information is achieved by iterating the selected wavelet base. In the classification of information, child wave space can be treated as feature space of pattern recognition. Feature extraction of information is achieved by weighting wavelet base and inner product of information vector. And then input these features to classifier [5]. Wavelet network combines the good time-frequency localized property of WT with self-learning function of traditional neural network. Therefore, it has the good approaching and fault tolerant abilities. Figure 1 is its topological structure.

Supposed network has N input nodes, M output nodes and the total training sample is L. Then, for the l th sample, the m th output is:

$$v_{lm} = \Phi(u_l) = \Phi(\sum_{k=1}^{K} w_{km} \sum_{t=1}^{N} f_l(t_i) \psi(\frac{t_i - \tau_k}{a_k})) \tag{3}$$

Where: m=1,2,···M； l =1,2,···L

One important characterstic of wavelet neural network training algorithm is learning function, which can adjust automatically each node weight to satisfy the decided goal according to the relationship of input and output of certain amount samples.

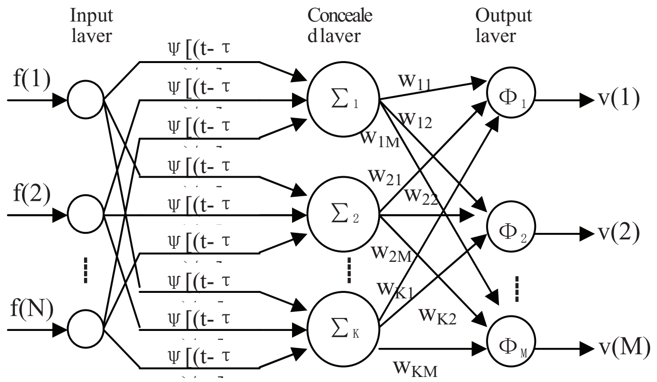

Figure1 Wavelet network topological structure

3.Fuzzy wavelet neural network model and its algorithm

Based on the features of neural network, one or more layers nerve cell (concealed layers nerve) are added between input layer and output layer [7]. Considering mutiperceptron only permit adjust one layer connection weight number, we use three layers network. And the weight number of nerve cell of input layer and concealed layer is fixed (can’t adjust), but the connection weight number of the concealed layer and output layer can be adjusted. It can be proved that ideal output can be achieved if the cell number between concealed layers is enough in the neural network [8]. According to this case, we select the nodes number of input layer as attribute number, the nodes number of output layer as scheme number. The nodes number of concealed layer is determined by practical needs. Input layer is responsible for proceeding input data wavelet decomposition, the weight number is fixed to 1. Output layer is activation function, and takes S type function

$\Phi(u_i) = \dfrac{1}{1+e^{-u_i}}$ as activation function. Takes the common Morley function: $\psi(t) = \cos(1.75t)e^{-\frac{t^2}{2}}$ as wavelet mother function. Finally, the output results can be calculated by using formula $\widetilde{D} = \widetilde{\varpi} \otimes \widetilde{R} = (d_1, d_2, \cdots, d_m)$. See Figure 2.

For the formula (3), first, we must determine such network parameters: w_{km} (k=1,2⋯,K; m=1,2⋯,M) 、 τ_k 、 a_k. Thus takes, $E_l = \frac{1}{2}\sum_{m=1}^{M}(d_{lm} - v_{lm})^2$, $E = \sum_{l=1}^{L} E_l$, where d_{lm} is the desired output of $f_n(t)$, as training target function. And adopts the commonest gradient descent law as optimal method. Set $t' = \dfrac{t-\tau_k}{a_k}$, then $\Phi'(u_n) = \dfrac{\partial\Phi(u_n)}{\partial u_n} = \Phi(u_n)(1-\Phi(u_n))$,and gradient of E are:

$$G(w_{km}) = -\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{n=1}^{N}(d_{lm}-v_{lm})\Phi'(u_n)f_l(t)\cos(1.75t')e^{-\frac{t^2}{2}} \tag{4}$$

$$G(\tau_k) = -\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{n=1}^{N}((d_{lm}-v_{lm})\Phi'(u_n)f_l(t)w_{km}(1.75\sin(1.75t')e^{-\frac{t^2}{2}}\frac{1}{a_k} + \cos(1.75t')e^{-\frac{t^2}{2}}\frac{t'}{a_k}) \tag{5}$$

$$G(a_k) = -\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{n=1}^{N}((d_{lm}-v_{lm})\Phi'(u_n)f_l(t)w_{km}(1.75\sin(1.75t')e^{-\frac{t^2}{2}}\frac{t'}{a_k} + \cos(1.75t')e^{-\frac{t^2}{2}}\frac{t'^2}{a_k}) = G(\tau_k)t' \tag{6}$$

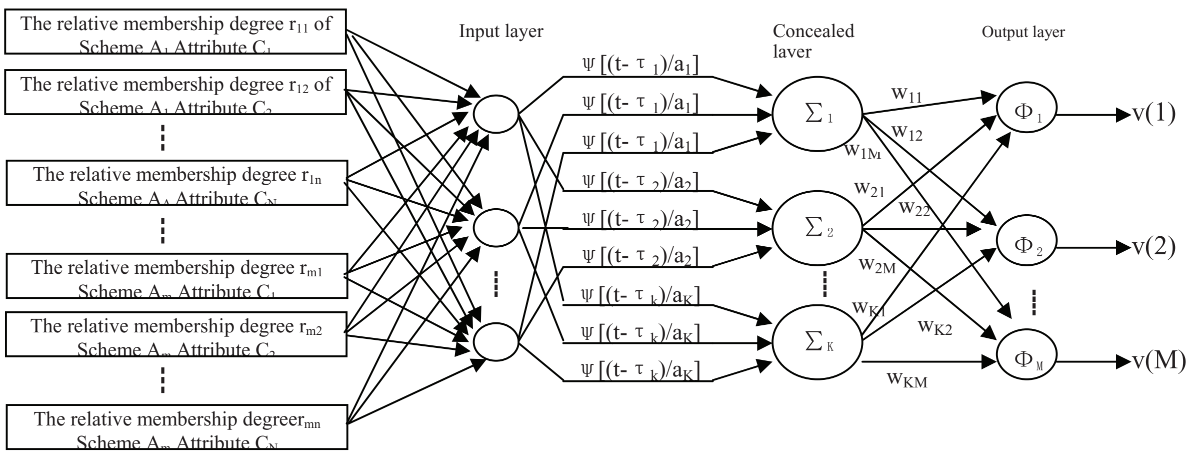

Figure 2 Prediction model based on fuzzy wavelet neural networks

Let $\vec{w} = (\vec{w}_1, \vec{w}_2, \cdots, \vec{w}_k) = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1m} \\ w_{21} & w_{22} & \cdots & w_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ w_{k1} & w_{k2} & \cdots & w_{km} \end{pmatrix}^T$, then $\vec{G}(\vec{w}) = (G(\vec{w}_1), G(\vec{w}_2), \cdots, G(\vec{w}_k))$

Suppose $\vec{Q}(\vec{w})_i$ is the search direction of $\vec{w}$ in ith loop, then

$$\bar{Q}(\vec{w})_i = \begin{cases} \bar{G}(\vec{w})_i & i=1 \\ -\bar{G}(\vec{w})_i + \dfrac{\bar{G}(\vec{w})_i[\bar{G}(\vec{w})_i]^T}{\bar{G}(\vec{w})_{i-1}[\bar{G}(\vec{w})_{i-1}]^T}\bar{Q}(\vec{w})_{i-1} & i \neq 1 \end{cases} \tag{7}$$

The same can get the search direction of $\bar{Q}(\vec{\tau})_i$ and $\bar{Q}(\vec{a})_i$ in ith loop. According to gradient descent law, $\vec{w}$, $\vec{\tau}$ and $\vec{a}$ can be adjusted by:

$$\begin{cases} \vec{w}_{i+1} = \vec{w}_{i+} + \alpha_w \bar{Q}(\vec{w})_i \\ \vec{\tau}_{i+1} = \vec{\tau}_{i+} + \alpha_\tau \bar{Q}(\vec{\tau})_i \\ \vec{a}_{i+1} = \vec{a}_{i+} + \alpha_a \bar{Q}(\vec{a})_i \end{cases} \tag{8}$$

Based on analysis mentioned before, we have programmed corresponding program to realize it. If taking the typical previous similar decision scheme as learning case, the wavelet neural network can store the experience and reasoning mechanism of experts proceeding multiple attribute decision-making, like a black box [9]. When a new scheme should be assessed, what we should do is to give a group of input, that the attribute features of scheme. And the program will calculate the assessment value, as a good and bad standard for assessing the scheme.

4.Experimental design

In order to verify the feasibility and effectiveness of this method, we take the actual historic consumption of power system as an example, and carry out electric energy consumption forecasting simulation using the above model FWN.

We take the maximum temperature, minimum temperature, humidity and weather conditions, the biggest, the smallest and the average consumption before testing day as input data. There is a electricity consumption value of testing period as output data [10]. We take point forecast in this article. And we take historical data six weeks ago to train the network. Learning rate η=0.25, inertia constant α=0.6, learning error E=0.0005%, check scale mi value (*mi* =-1, 0, 1, 2, 3, 4), that is, there are 6 fuzzy rules. In order to compare the merits and demerits of the model, we predict the electric energy consumption using Grey models under the same pattern of training, learning rate and constant inertia [11]. Take 2003-2006 as the forecasting years, the results in Table I, also gives the results of a few years when the load, temperature and weather conditions of the most dramatic changes. See Table II.

From the results we can see that the electric energy consumption forecasting accuracy based on fuzzy wavelet neural network has been significantly improved, at the same time proved this method is totally feasible. From Table 1 we can also find that the forecasting relative error in fuzzy wavelet neural network changes uniformly, which suggests that its generalization increase significantly neural network. From Table 2 we can see fuzzy wavelet network can fit with the electric energy consumptin and weather factors more closely. Therefore we can get more reliable forecasting results.

TABLE I. ELECTRIC ENERGY CONSUMPTION FORECASTING RESULTS OF A CERTAIN POWER NETWORK

		FWNN Model		**GM(1,1) Model**	
Year	Electric Energy Consumption	Forecasting Value Kwh	Relative Error %	Forecasting Value Kwh	Relative Error %
1983	13.4	13.63	1.75	21	56.72
1984	15.3	15.30	-0.02	23.5	53.59
1985	21.3	20.78	-2.46	26.2	23.00
1986	23.2	22.75	-1.92	29.3	26.29
1987	26.4	26.87	1.79	32.7	23.86
1988	31.2	31.91	2.29	36.6	17.31
1989	35.3	34.52	-2.22	40.9	15.86
1990	42.4	42.75	0.82	45.6	7.55
1991	46.9	45.30	-3.41	51	8.74

1992	54.6	53.82	-1.43	57	4.40
1993	61.2	62.35	1.88	63.6	3.92
1994	72.7	73.35	0.89	71.1	-2.20
1995	83.5	81.50	-2.4	79.4	-4.91
1996	93.1	94.52	1.53	88.7	-4.73
1997	101.8	102.44	0.63	99.1	-2.65
1998	106.6	108.25	1.55	110.7	3.85
1999	118.2	117.14	-0.9	123.7	4.65
2000	132.4	134.93	1.91	138.2	4.38
2001	144.6	143.02	-1.09	154.4	6.78
2002	156.3	155.17	-0.72	172.5	10.36
2003	173.7	175.66	1.13	192.7	10.94
2004	190.2	192.16	1.03	215.3	13.20
2005	216.7	214.03	-1.23	240.5	10.98
2006	249.4	243.46	-2.38	268.7	7.74

TABLE II. FORECASTING DATA

Forecasting Year	FWNN MAPE/%	GM(1,1) MAPE/%
1995	1.79	19.10
1997	1.70	17.05
2003	1.56	14.13
2006	1.56	13.70

$$\left(MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\hat{y}_t - y_t}{y_t}\right| \times 100\ \% \right)$$

5.Conclusions

The electricity consumption is forecasted by applying GM(1,1), but the precision is not very ideal. In order to overcome the disadvantages of the present prediction methods for electric energy consumption forecasting, the electrical consumption prediction model based on wavelet neural network is introduced in this paper, which can combine subjective attribute weight number with objective attribute weight number better, and can self-adjust by using the previous typical case[12]. It has have been shown the excellent results of a method for electric energy consumption forecasting in city based on a FWNN. The new energy predictor presents a precision comparable to the better results reported in the literature. Good effects are achieved by simulation and programming, which have good practical value. Case analysis indicates that the method is right and feasible. The main virtue of this system is its simplicity, which is based on the fact that the developed tool is very simple and the resources for its application are tiny and available at modern automation systems.

Comparing with artificial neural network, fuzzy wavelet neural network prediction method does not only improve the precision of prediction, but also improves rate of convergence. Definitely, the algorithm presented in this paper has great potential and bright future in other fields.

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