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Application of a Hybrid Algorism Combining Fuzzy Theory and Neural Network for Heating Load Forecasting

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Abstract: Accurate load forecasting has a great significance for heating companies to make the best decisions in terms of unit commitment, generation and maintenance planning, etc. It is necessary that heating generation companies have prior knowledge of future demand with great accuracy. A flexible algorithm based on Fuzzy Logic (FL) and artificial neural network (ANN) is presented to cope with optimum heating load forecasting in noisy, uncertain and complex environments. It is concluded that the selected newly method considerably outperform the WNN models in terms of Mean Absolute Percentage Error (MAPE). The proposed flexible FL-ANN algorithm can be easily applied to complex, non-linear and uncertain datasets, such as central heating system.

Key words: Load forecasting, artificial neural networks, fuzzy logic, central heating system

INTRODUCTION

Accurate load forecast provides system dispatchers with timely information to operate the system economically and reliably. It is also necessary because availability of heat supplied is one of the most important factors for improving heat supply effect.

Several methods for short-term load forecasting have been suggested and implemented. These include time-series models of ARMA type (Amjady, 2001; Wiklund, 1991), Kalman filters (Arvastson, 2001; Infield and Hill, 1998), Linear Regression (LR) technique (Forrester and Wepfer, 1984), neural-network (ANN) model (Kawashima *et al*., 1996), grey model (Hwang *et al*., 1997) and wavelet neural network (Kelo and Dudul, 2012). However, no single one has performed well enough because each model can take a few or usually only one relevant factor into consideration. In all these algorithms, ANNs have been broadly applied to man y forecasting problems due to their capability in discovering hidden relationships in data. Single hidden layer network based on Back-Error Propagation (BEP) learning is the most widely used model form for forecasting (Zhang and Qi, 2005). FL methods are appropriate for the situations with incomplete data and require fewer observations than other forecasting models (Hong and Yi, 2003). For the combined forecasting method (Kodogiannis and Anagnostakis, 2002), it cannot make use of the full capability of residual subspace. In addition, using all data would compromise the robustness of the prediction scheme. Recently, with the developments of artificial intelligence, alternative solutions to the short-term heating load forecasting problem have been proposed. Expert systems have been successfully applied to it (Kodogiannis and Anagnostakis, 2002). Many researchers have been carried out on the application of ANN techniques and fuzzy logic to the load forecast (Badri *et al*., 2012). The combined forecasting method is that FL and ANN are mashed together, ANN is given fuzzy human thought. It is somewhat like ANN in structure, yet it is fuzzy in function.

T-S FUZZY MODEL

Fuzzy model often manifests as fuzzy rules, the key of fuzzy modeling is to obtain which depending on experts' opinion, building manipulator control behavior model, constructing the model of controlled object and organizational learning respectively. For the central heating system, a nonlinear dynamical system, the self-learning way is adopted to adjust the fuzzy rule constantly in order to improve accuracy of fuzzy modeling. The paper adopt T-S fuzzy model which has been attracted by many scholars.

The fuzzy model which can not only to be updated automatically but to revise membership function of fuzzy subset continuously, has strong self-adaptation ability. Its general form for fuzzy rule is as follows:

$$R_i: \text{If } x_1 \text{ is } A_1^i, x_2 \text{ is } A_2^i, \ldots, x_k \text{ is } A_k^i$$

then:

$$y_i = p^i_0+p^i_1x_1+...p^i_kx_k$$

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where, R_i is the ith fuzzy criteria; A^i_j is fuzzy subset of system, membership function could be triangle, triangle and Gaussian; $p^i_j(j = 1, 2,..., k)$ is fuzzy system parameter; y_i is output obtained according to fuzzy rules, input part that is if part, is fuzzy, output part, namely, then part, is certain. The fuzzy reasoning shows that output is linear combination of input.

With regard to input $x = [x_1, x_2,\ldots, x_k]$, the membership of each input variable xi is computed by fuzzy rule:

$$\mu_{A^i_j} = \exp\frac{-(xj - c^i_j)^2}{b^i_j} \quad j = 1, 2,\ldots, k;\ i = 1, 2,\ldots, n \tag{1}$$

where, $\mu_{A^i_j}(x_j) \in [0,1]$, its value is more closer to zero, it is showed that x_j belongs to fuzzy subset; moreover, the parameters c^i_j, b^i_j represent the central and width of subordinating degree function; k represents the input parameter; n is the number of fuzzy subsets.

Every subordinating degree is obtained by fuzzy computing, fuzzy operator is adopted by a product of operator:

$$\varpi^i = \mu_{A^1_j}(x_1) * \mu_{A^2_j}(x_2) * \cdots * \mu_{A^i_j}(x_k) \quad i = 1, 2,\ldots, n \tag{2}$$

The output yi of fuzzy model is calculated using the following equation:

$$y^i = \frac{\sum_{i=1}^{n} \varpi^i (p^i_0 + p^i_1 x_1 + \cdots + p^i_k x_k)}{\sum_{i=1}^{n} \varpi^i} \tag{3}$$

A HYBRID NETWORK COMBINING FL WITH ANN

By reviewing literature on this area Inspired, a hybrid algorithm based on ANN and FR is proposed for short-term forecasting of heating load. The hybrid algorithm, combining the advantages of both neural networks and fuzzy logic, whose structure is shown in Fig. 1.

As can be seen from the Fig. 1, the hybrid network consists of five information layers. The first acts as input layer, its node is the number of input variable; the second which the membership functions layer of input variable, is the fuzzification layer in order to achieve fuzzification of input variable, it can be obtained by the formula (Arvastson, 2001); the third is “and” layer, its node is the number of fuzzy rules, each node in the layer is only connected with one of m and n nodes, the total nodes is m×n, namely, m×n rules; the fourth is “or” layer, the node equals to the number q of dividing ambiguity, this style to the third is completely interconnection. w_{kj} represents the connective weights, where, $k = 1, 2,\ldots q$; $j = 1, 2,\ldots, m\times n$ (the weight represent confidence coefficient of every rule, is fully adjustable in training); the fifth layer is defuzzification, the nodes is the number of output variable, the connection to the fourth layer is also completely interconnection, the layer is to transform the output of each node for above layer into the exact value of output variable. In the whole network structure, the third and fourth are viewed as fuzzy reasoning layer.

THE ANALYSIS OF HEATING LOAD FORECASTING

The section predicts the heating load by the aforementioned method using the historical data from a

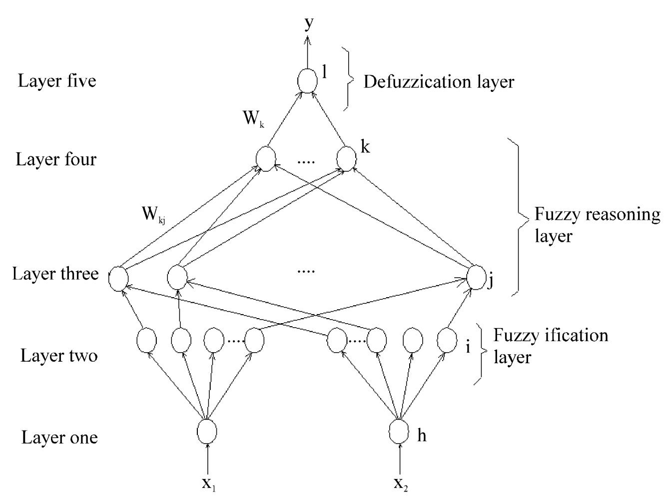

Fig. 1: The structure of fuzzy neural network

local heat source and from analyses error, compares the accuracy with WNN. A kind of algorithm more suitable for heating load prediction was found.

It is difficult to predict heat supplied through a single value function of outdoor temperature effected directly considering that the nonlinear characteristic of heating system is caused great thermal inertia, time delays and attenuating property caused heat loss of pipe network. It is firstly established in the paper that some parameters reflecting system characteristic which is used to recognize the patterns of system, cooperate with direct acting factor, such as outdoor temperature, to forecast heat supplied. Each influence factor is firstly analysed by statistical method in order to identify the relationship between influence factor and heat supplied and improve the accuracy of the prediction model.

The establishment of model: The heat supplied is predicted by using the network structure of the third section established. The data, 128 days from Handan, is divided into two section, one part among is the first 121 days data which is used to train the network established, another part is the later 7 days data which is used to test the network. The relevant parameters reflecting internal characteristic of system of heat supplied adopt the sequence of the moment t-1, t-2, t-3, the external parameters, such as outdoor temperature, adopt the future value to predict heat load. The neuron of input layer is 6, the hidden layer is 10 that is 10 membership function, the output layer is 1; the initial centers and widths of membership functions of the fuzzification layer are obtained by network randomly; the number of iterations which is 100 is decided by many trials.

The analysis of result: The samples data processed are used to train and predict the heating load as input parameters. The result is shown in Fig. 2 and 3.

Figure 2 indicates that top 121 data of all time sequence is used to train the hybrid network. It can be seen that these training data can be fitted well with the new method combining fuzzy theories and neural network. There is some difference in some big fluctuations of data measured, the reasons could be for human disturbance in operating. But there is fine coincidence and little error between prediction data and experimental data in the most of sample points. The later 7 time sequence is used to test the network trained previously, the result is shown in Fig. 3, it can be seen that values predicted are very close to the practice. The error is analysed by the Mean Absolute Percentage Error (MAPE). The error is shown in following Eq. 4:

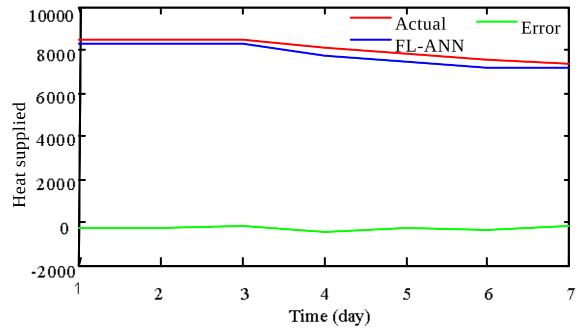

Fig. 2: The comparison of forecasting load with FL-ANN in training

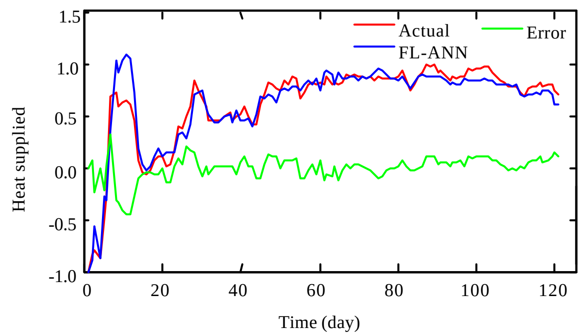

Fig. 3: The comparison of forecasting load with FL-ANN in forecasting

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} PE_i \tag{4}$$

$$PE_i = \frac{y_i - \hat{y}_i}{y_i}$$

where, PE_i is the Relative Error (RE); n is the sample number; yi is the actual value; $\hat{y}_i$ is predicted value.

The comparison with WNN: Interest in WNN based on multi-scale analysis is increasing because it can effectively extract the local information of a signal, has the strong learning ability and higher precision. WNN is adopted to predict heat supplied, the same data with the hybrid network is used, the predicting result is shown in Fig. 4.

It can be seen from Table 1 that the MAPE of the hybrid algorism is 0.037, accuracy rate is 0.963. Comparison with WNN, the error decreases by 34.7%, the precision increases by about 3% points. The prediction value used by the hybrid algorism is more close to the measured values than WNN and its error is also smaller.

Table 1: The comparison and analysis with WNN

		The hybrid algorism			WNN		
Prediction time	Measured value	Prediction value	PEi	MAPE	Prediction value	PEi	MAPE
2012.3.9	8529	8264.8	0.030977	0.037212	8193.8	0.039301	0.0675
2012.3.10	8514	8238.1	0.032405		8011.8	0.058985	
2012.3.11	8467	8257.0	0.024802		7874.9	0.069930	
2012.3.12	8162	7678.0	0.059299		7751.4	0.050306	
2012.3.13	7805	7498.1	0.039321		7197.7	0.077809	
2012.3.14	7515	7170.9	0.045788		6683.8	0.110605	
2012.3.15	7347	7142.1	0.027889		6865.3	0.065564	

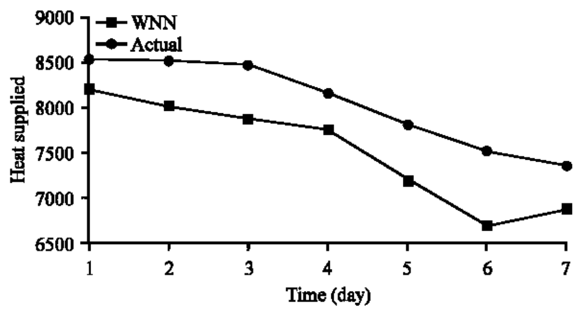

Fig. 4: The comparison of forecasting load with WNN in forecasting

This illustrates the hybrid algorism which brings its ability of processing non-linear problem into full play and the ability of fuzzy recognition for complicated nonlinear systems, the prediction can well tack the practice value. The algorism is fully satisfactory to the need of engineering.

CONCLUSION

The study presents a hybrid algorism which combines fuzzy logic with neural network, has the advantages of both. It is more specifically suited to the nonlinear and uncertainty system of central heating. The influence factors which are divided into internal factor and external factor, is firstly analysed through using statistical theory to identify the correlation with heat supplied. Internal factor reflects the characteristic of the heating system itself. The processed data is adopted as training and predicting heat supplied through using FL-ANN. The comparison with WNN indicates that the hybrid algorism is more suitable for the prediction of heat load and should be fully satisfactory to the need of engineering.

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