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Research Article

Artificial Neural Network and ANFIS Based Short Term Load Forecasting in Real Time Electrical Load Environment

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Abstract

An efficient and accurate electrical power Short Term Load forecasting plays a vital role for economic operational planning of both the electricity markets as well as regulated power systems. Till date many techniques and approaches have been presented for STLF in the literature. However there is still an essential need to develop more efficient and accurate load forecast model. This paper uses hourly load data of three years from 2005-2007, and weather data such as temperature, wind speed and humidity for the same years. Forecasting will be of load demand for coming hour based on input parameters at that hour. In regard to the influence of real-time electricity market on short-term load, a model to forecast short term load is established by combining the artificial neural network (ANN) with the adaptive neural fuzzy inference system (ANFIS). The model first makes use of the nonlinear approaching capacity of the FFBP network to forecast the load on the prediction day with no account of the factor of electric load, and then, based on the recent changes of the real-time load, it uses the ANFIS system to adjust the results of load forecasting obtained by ANN network. This system integration will improve forecasting accuracy and overcome the defects of the ANN network.

Keywords: *STLF, Weather parameters, Artificial Neural Network, Short Term Load Forecasting, ANFIS*

1. Introduction

Short-term load forecasting accuracy is very important for the power system. STLF is very essential task for power system operation because it can help the electric utility to make important decisions including unit commitment, load switching etc. It also described about STLF survey and role of STLF in on line scheduling and security functions of an energy management system.

For STLF several approaches utilizing statistical methods and Artificial Intelligence (AI) techniques have been reported in the literature. The statistical methods, such as autoregressive moving average, linear regression, stochastic time series, and general exponential smoothing are hard computing techniques based on the exact model of the system and utilize linear analysis. Short-term load forecasting (STLF) is an important guideline for safe scheduling and economic managing of power systems. Under the conditions dictated by electricity markets, electric utilities have to establish reasonable economic models and competitive real-pricing according to accurate and fast forecasting results of a short-term load. And thus, for a long time, STLF has been under great focus and various algorithms have been put forward (P. A. Mastorocostas *et al*, 1999; H. S. Hippert *et al*, 2001; S. J. Huang *et al*, 2003; A. J. R. Reis *et al*, 2005; S. Fan et al, 2006). For example conventional techniques include fuzzy logic inference (K. Alireza *et al*, 2002; M. Widjaja *et al*, 1999; V. Lyer *et al*, 2003), regression techniques (A. D. Papalexopoulos *et al*, 1990), time series approaches (M. T. Hagan *et al*, 1987; S. P. Michanos *et al*, 2003; Q. C. Lu *et al*, 1989), expert system based methods (S. Rahman *et al*, 1988) are also commonly used. As for forecasting under real-time price conditions, various types of artificial neural network (ANN) have been proposed for short-term load forecasting (A. Chen Hong *et al*, 2001; C. S. Chang *et al*, 1998). They enhanced the forecasting accuracy compared with the conventional time series and regression methods.

The combination of artificial neural network, Genetic algorithm, and Fuzzy logic methods are proposed for adjusting short term load forecasting of electric of electric system. Genetic algorithm is used for selecting better rules (J. S. R. Jang, 1993; Wang Wu *et al*, *2009*; Gwo-Ching Liao *et al*, 2006; Gwo-Ching Liao *et al*, 2004; Feng Han *et al*, 2010). The papers show that they give more accurate results and faster processing than other forecasting methods.The work by (Madasu Hanmandlu *et al*, 2010) presents two hybrid neural networks derived from fuzzy neural networks (FNN), wavelet fuzzy neural network (WFNN) using the fuzzified wavelet features as the inputs to FNN and fuzzy neural network (FNCI) employing the Choquet integral as the outputs of FNN. The results of the two hybrid networks using Indian utility data are compared with ANFIS and other conventional methods.

ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned

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(adjusted) using either a back-propagation algorithm alone or in combination with a least squares type of method. This adjustment allows fuzzy systems to learn from the data it is modeling (J. P. S. Catlao *et al*, 2010; Z. Yun *et al*, 2008).

This paper combines a neural network and a fuzzy system for STLF in the real-time load environment. Section 2 reveals the relationship between weather parameters and short-term load. In Section 3, daily loads are firstly forecasted by FFBPNN with considering the weather parameters. An adaptive neural fuzzy inference system is introduced to adjust the forecasting results according to the change of the latest electricity demand in Section 4. Section 5 is about the results and discussion of the proposed methods. Finally, a conclusion is reached in Section 6.

2. Technical analysis of real time data and STLF

It applies a real history load data to predict the load of the next hour. A case study on STLF of MSEB of Maharashtra state, India is performed. The historical electrical load data of three years, 2005-2007 is used in the proposed model.

The weather data like temperature, wind speed and humidity is also considered for the same years. Fig.1 shows weekly load curve from which it is seen that the load is affected by temporal variations, abrupt increase in demand, outages or other random disturbances.

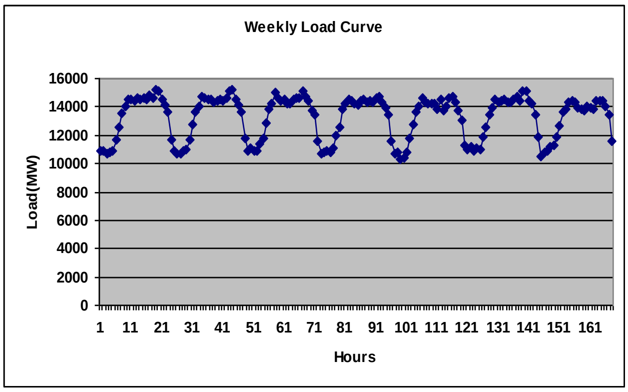


Fig. 1 Weekly Load Curve

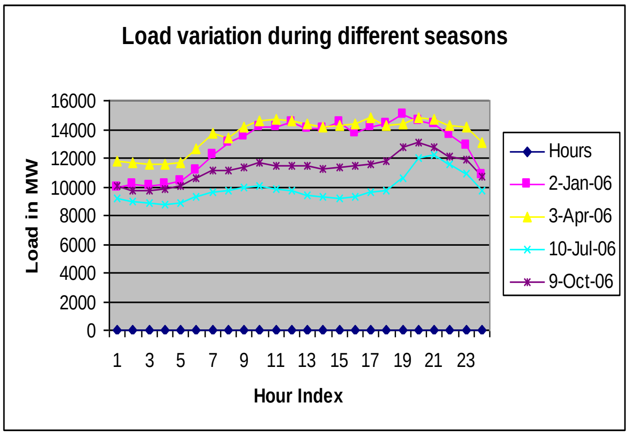


Fig 2 Load Variation during Different Seasons

Fig. 2 clearly shows load variation during different seasons. There is strong correlation between the behavior of the power consumption and weather variables as temperature, relative humidity, wind speed, humidity, and social celebrations. The graph in Fig. 3 shows a scatter plot between the maximum temperature and consumption in summer (May 2007). In Fig. 4 monthly humidity readings during morning and evening hours are given for the three years.

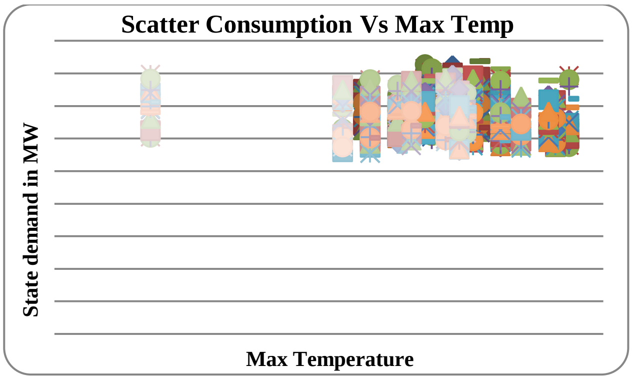


Fig.3 Scatter plot between Max Temperature and the Consumption in May 2007.

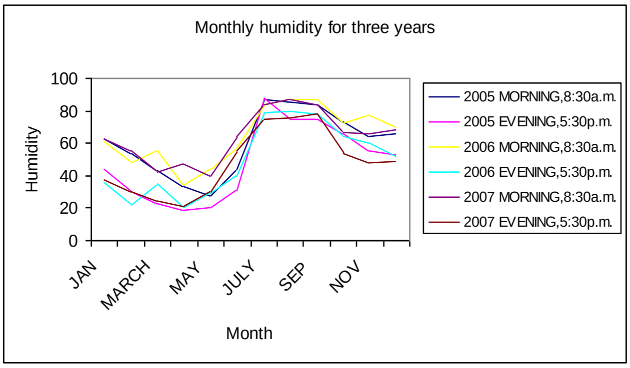


Fig 4 Monthly Humidity for three years

3. Brief introduction about back-propagation neural network

1. Artificial Neural Network

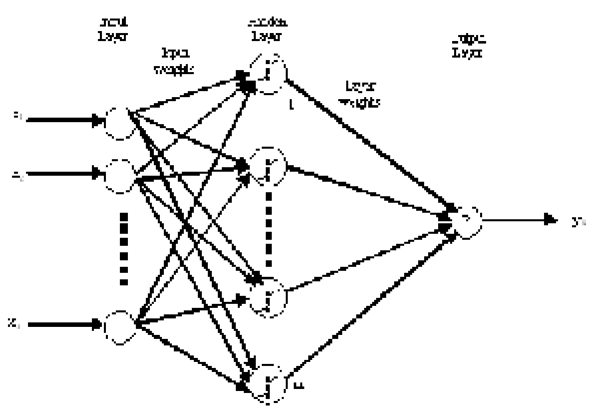


Fig. 5 Feed-forward artificial neural network with single output unit

ANN is designed by using the multilayer perceptron (MLP) and back-propagation learning technique. The three layers connect to feed-forward back-propagation are input layer, hidden layer and output layer as shown in Fig. 5.

The back-propagation learning algorithm is the most frequently used method in training the networks, and proposed as an electrical load forecasting methodology in this paper. For the completeness of the paper, the back-propagation algorithm will be introduced briefly.

In a typical NN model, an activation function is applied to the summation of weighted inputs at the hidden layer neurons and therefore the output of jth neuron of a hidden layer can be computed as

$$O_j = f_{HL}\left[\sum_{i=1}^{n} w_{ij}\, x_i\right] \quad (1)$$

Where n is the total no of inputs (excluding the bias) applied to the hidden layer neuron, w_{ij} is the weight connecting i^{th} input neuron to j^{th} hidden layer neuron and x_i is the input signal.

The most common form of activation function, f_{HL}, used for the hidden layer neurons in NN models is a sigmoid function.

$$f(u) = \frac{1}{1+e^{-au}} \quad (2)$$

Where u is the input and '*a*' is the slope parameter of the sigmoid function. Each output of hidden layer neurons is multiplied with the corresponding layer weight. The activation function f_{OL} is applied to the weighted summation of *m* hidden layer neurons yields the output y_k from the output layer neuron.

$$y_k = f_{OL}\left[\sum_{j=1}^{m} w_{jk}\, O_j\right] \quad (3)$$

Where *m* is the total number of inputs (excluding the bias) presented to the output layer neuron *k* , and w_{jk} is weight connecting j^{th} hidden neuron to k^{th} output layer neuron. Fig. 5 illustrates the NN model with single output unit (k=1). The linear activation function, f_{OL} generally used for output layer in NN model.

2. ANN architecture for STLF

The schematic diagram for the proposed model is shown in Fig. 6. There are total 8 neurons in the input layer of designed network. The first neuron is used to define the day type of the forecast. The second neuron is used to define previous hour's load. The last 6 neurons are used to take the effect of maximum and minimum values of temperature, wind speed and humidity into consideration.

The output layer of network comprises of only 1 neuron. This neuron corresponds to one hourly load for forecasting.

The number of neurons in the input or output layer is already fixed due to the selected input and output data. The number of neurons in the hidden layer is determined such as we test the network with a small number of neurons and then increase the number of neurons step by step until the training process is qualified.

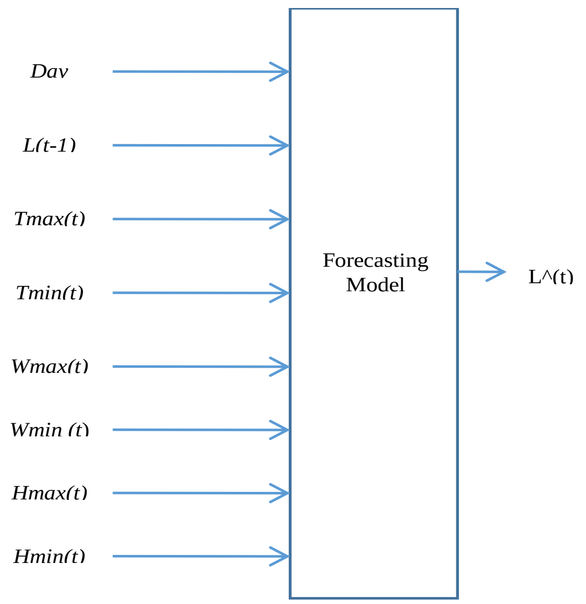


Fig. 6 Schematic forecasting model

The STLF procedure for the designed ANN model is given below.

a) Input variable selection: as mentioned earlier identification factors affected load patterns is the first important step for making an acceptable load forecasting.
b) Data Pre-processing: unacceptably recorded data and observation errors are unavoidable. Hence usually a statistical method is used to identify bad and regular data and discard or adjust these data.
c) Scaling: since there are very different ranges for variables; convergence problems may be caused by direct use of input data. All input and output data are scaled to be in the [0, 1] range. Following scaling method is used in this research work.

$$Normalized\ Value = \frac{Actual\ Value}{Maximum\ Value} \quad (4)$$

d) Training: when the neural network is started; system initializes weights and biases of each layer. The connection power among the interior nodes can be adjusted by network. Finally network learns the appropriate transformation between past inputs and outputs from the training cases. In this paper feed-forward back-propagation with three layers is used. TRAINLM is used as training function. TANSIG is used as transfer function from input layer to hidden layer and PURELIN is used from hidden layer to output layer.
e) Simulation: the forecasting output is simulated using the trained neural network.
f) Error Analysis: since load characteristics vary, error analysis is important for the forecasting process. Hence, the following Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE) are used here for after-the- fact error analysis.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|L_a - L_f|}{L_a} \times 100 \quad (5)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(L_a - L_f)^2 \quad (6)$$

where L_a denotes the actual load value, L_f is the forecasted load value, and N represents the number of observations or data points.

g) Post-Processing: the neural network output need to be de-scaled for generating the preferred forecasted loads.

4. Adaptive neuro fuzzy inference system

1. ANFIS

ANFIS is a class of adaptive multilayer feedforward networks, applied to nonlinear forecasting where past samples are used to forecast the sample ahead. ANFIS incorporates the self-learning ability of NN with the linguistic expression function of fuzzy inference.

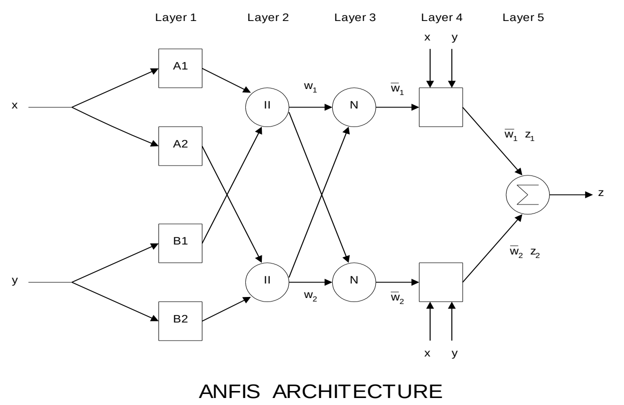


Fig.7 ANFIS Structure

The ANFIS architecture is shown in Fig.7. The ANFIS network is composed of five layers. Each layer contains several nodes described by the node function. Let O_i^j denote the output of the i^{th} node in layer j.

In layer 1, every node i is an adaptive node with node function

$$O_i^1 = \mu A_i(x), \quad i = 1,2 \quad (7)$$

Or

$$O_i^1 = \mu B_{i-2}(y) \quad i = 3,4 \quad (8)$$

Where x (or) y is the input to the i^{th} node and A_i (or B_{i-2}) is a linguistic label associated with this node. The membership functions for A and B are usually described by generalized bell functions, e.g.,

$$\mu A_i(x) = \frac{1}{1+\left|\frac{x-r_i}{p_i}\right|^{2q_i}} \quad (9)$$

where $\{p_i, q_i, r_i\}$ is the parameter set.

Any continuous and piecewise differentiable functions, such as triangular-shaped membership functions, are also qualified candidates for node functions in this layer. Parameters in this layer are referred to as premise parameters.

In layer 2, each node Π multiplies incoming signals and sends the product out

$$O_i^2 = w_i = \mu A_i(x)\mu B_i(y), \quad i = 1,2 \quad (10)$$

Hence, each node output represents the firing strength of a rule.

In layer 3, each node N computes the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \quad (11)$$

The outputs of this layer are called normalized firing strengths.

In layer 4, each node computes the contribution of the i^{th} rule to the overall output

$$O_i^4 = \bar{w}_i z_i = \bar{w}_i(a_i x + b_i y + c_i), \quad i = 1,2 \quad (12)$$

Where $\bar{w}_i$ is the output of layer 3 and $\{a_i, b_i, c_i\}$ is the parameter set. Parameters of this layer are referred to as consequent parameters.

In layer 5, the single node $\sum$ computes the final output as the summation of all incoming signals

$$O_i^5 = \sum \bar{w}_i z_i = \frac{\sum_i w_i z_i}{\sum_i w_i}, \quad i = 1,2 \quad (13)$$

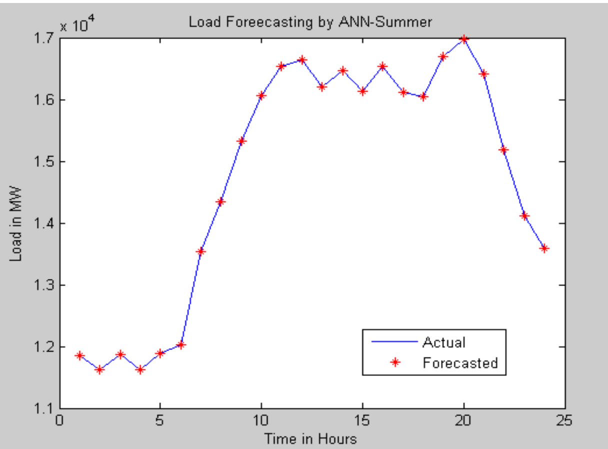
Thus, an adaptive network is functionally equivalent to a Sugeno-type fuzzy inference system.

2. Load adjustment by ANFIS

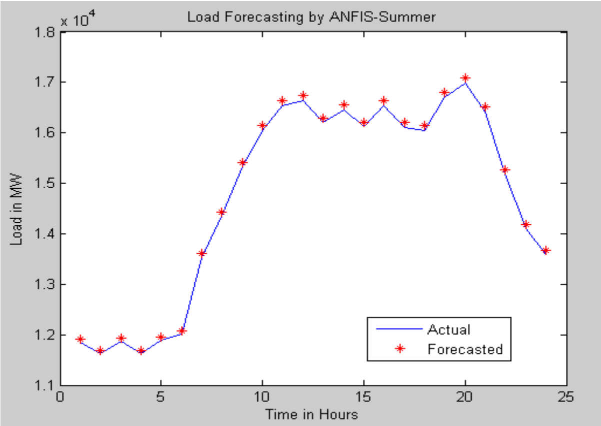
ANFIS is used to establish a load adjustment system so that it can improve the accuracy of forecasting results of FFNN effectively under the environment of real-time load and weather data.

5. Results and discussion

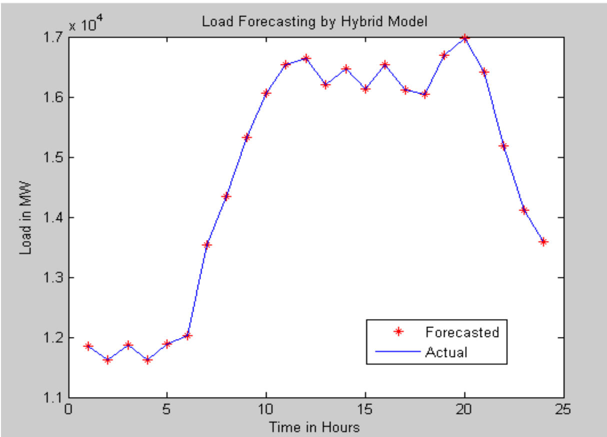
Case study for the proposed method was carried out for



(a)



(b)



(c)

Fig. 8 Actual and Forecasted Load for three models

forecasting of one hour ahead electric load using a historical data of MSEB. MATLAB 7.10 is used for simulation purpose. Results for different models are shown in Fig. 8. (a), 8 (b) and 8 (c). And comparison of load forecasting error by ANN, ANFIS and ANN-ANFIS hybrid model is shown in Table I. Mean absolute percentage error (MAPE) of forecasting by ANN-ANFIS is also comparatively less than ANN and ANFIS model.

Table 1 Comparison of error of ANN, ANFIS and ANN-ANFIS

Compared Error	ANN	ANFIS	ANN-ANFIS
MAPE	0.0044	0.56356	0.000396
MSE	0.00096	0.1711	0.000788

Conclusion

This work investigated the ability of neural network to predict the hourly load using ANN algorithm to adjust weights and biases in order to minimize the error objective function of a neural network to obtain a reasonable active, intelligent solution. Short term load forecasting using ANN shows its ability to minimize the error with high efficiency. In this study, it was found that selecting proper numeric values of network parameters, input data that affect the performance accuracy of the network. The proposed method makes full use of the transaction capability of ANN in dealing with non-linear problem as well as results correcting capability of ANFIS. The experimental evaluations have demonstrated calculation accuracy, strong practicability, feasibility, and effectiveness of the proposed load forecasting scheme. The results show the correctness of the model.

References

P. A. Mastorocostas, J. B. Theocharis, and A. G. Bakirtzis(1999), Fuzzy modeling for short-term load forecasting using the orthogonal least squares method, *IEEE Trans. Power Syst.*, vol. 14, no. 1, pp. 29–36.

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

S. J. Huang, K. R. Shih(2003), Short-term load forecasting via ARMA model identification including non-Gaussian process considerations, *IEEE Trans. Power Syst*., vol. 18, no. 2, pp. 673–679.

A. J. R. Reis and A. P. A. da Silva(2005), Feature extraction via multi-resolution analysis for short-term load forecasting, *IEEE Trans. Power Syst*., vol. 20, no. 1, pp. 189–198.

S. Fan and L. Chen (2006), Short-term load forecasting based on adaptive hybrid method, *IEEE Trans. Power Syst*., vol. 21, no. 1, pp. 392–401.

K. Alireza, Z. Enwang, and H. Elragal (2002), A neuro-fuzzy approach to short-term forecasting in a price-sensitive environment, *IEEE Trans. Power Syst*., vol. 17, no. 4, pp. 1273–1282.

M. Widjaja and W. Mielczarski (1999), A fuzzy-based approach to analyze system demand in the Australian electricity market, in Proc. *IEEE Power Eng. Soc. Summer Meeting*, Edmonton, AB, Canada, vol. 2, pp. 918–923.

V. Lyer, C. Chefung, and T. Gedeon (2003), A fuzzy-neural approach to electricity load and spot-price forecasting in a deregulated electricity market, in Proc. *IEEE Region 10 Conf. Convergent Technology for the Asian-Pacific*, India, vol. 4, pp. 1479–1482.

A. D. Papalexopoulos and T. C. Hesterberg (1990), A regression-based approach to short-term system load forecasting, *IEEE Trans. Power Syst*., vol. 5, no. 4, pp. 1535–1544.

M. T. Hagan and S. M. Behr (1987), The time series approach to short-term load forecasting, *IEEE Trans. Power Syst.*, vol. 2, no. 3, pp. 785–791.

S. P. Michanos, A. C. Tsakoumis, P. Fessas, S. S. Vladov, and V. M. Mladenov (2003), Short-term load forecasting using a chaotic time series, in Proc. *Int. Symp. Signals, Circuits and Systems, SCS*, vol. 2, pp. 437–440.

Q. C. Lu, W. M. Grady, M. M. Crawford, and G. M. Anderson(1989), An adaptive nonlinear predictor with orthogonal escalator structure for short- term load forecasting, *IEEE Trans. Power Syst*., vol. 4, no. 1, pp. 158–165.

S. Rahman and R. Bhatnagar (1988), An expert system based algorithm for short-term load forecast, *IEEE Trans. Power Syst.*, vol. 3, no. 2, pp.392–399.

A. Chen Hong, C. Claudio, and A. Singh (2001), ANN-based short-term load forecasting in electricity markets, in Proc. *IEEE Power Eng. Soc. Winter Meeting*, vol. 2, pp. 411–415.

C. S. Chang and Y. Minjun (1998), Real-time pricing related short-term load forecasting, in Proc. *Int. Conf. Energy Management and Power Delivery, Raffles*, Singapore, vol. 2, pp. 411–416.

J. S. R. Jang (1993), ANFIS: Adaptive-network-based fuzzy inference system, *IEEE Trans. Syst., Man, Cybern*, vol. 23, no. 3, pp. 665–685.

Wang Wu, Wang Guozhi, Zhang Yuanmin, Wang Hongling (2009), Genetic Algorithm Optimizing Neural Network for Short-Term Load Forecasting, *2009 International Forum on Information Technology and Applications* ,pp. 583-585 .

Gwo-Ching Liao, Ta-Peng Tsao (2006), Application of a fuzzy neural network combined with a chaos genetic algorithm and simulated annealing to short-term load forecasting, *IEEE Transactions on Evolutionary Computation*, Volume 10**,** Issue 3, , pp 330 - 340.

Gwo-Ching Liao, Ta-Peng Tsao (2004), Novel GA-based approach and neural fuzzy networks application in short-term load forecasting, *IEEE Power Engineering Society General Meeting,* Vol.1, pp. 589 - 594.

Gwo-Ching Liao, Ta-Peng Tsao (2004), Integrated genetic algorithm/tabu search and neural fuzzy networks for short-term load forecasting, *IEEE Power Engineering Society General Meeting*, vol.1,pp1082 – 1087.

Feng Han, Qing Zhang, Xu Zhang, T. Li, (2010), Application of Fuzzy Neural Network to Power System Short Term load Forecast, *2010 International Conference on Computer Design and Application,* Vol. 2, pp.496-499.

Madasu Hanmandlu, Bhavesh Kumar Chauhan, (2010), Load forecasting using Hybrid Models, *IEEE Transactions on Power Systems.*

J. P. S. Catlao, H. M. I. Pousinho, V. M. F. Mendes, (2010), Hybrid Wavelet-PSO-ANFIS Approach for Short Term Electricity Prices Forecasting, *IEEE transactions on Power Systems*.

Z. Yun, Z. Quan, S. Caixin, L. Shaolan, L. Yuming, and S. Yang (2008), RBF neural network and ANFIS-based short-term load forecasting approach in real-time price environment, *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 853–858.