

# Short term electric load forecasting using Neuro-fuzzy modeling for nonlinear system identification

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**Abstract:** Electric load forecasting is a real-life problem in industry. Electricity supplier's use forecasting models to predict the load demand of their customers to increase/decrease the power generated and to minimize the operating costs of producing electricity. In addition to the conventional classical models, several models based on artificial intelligence have been proposed in the literature, in particular, neural network for their good performance. Other nonparametric approaches of artificial intelligence have also been applied. Nevertheless, all these models are inaccurate when used in real time operation. The purpose of this paper is to present a short term electric load forecasting model using an adaptive neuro-fuzzy inference system (ANFIS). We discuss in detail how ANFIS is successfully applied to weekly load forecasting with respect to different day types. The input-output data pairs used are historical electricity load including losses of metropolitan France of the year 2009 obtained from the RTE website. Results and forecasting performance obtained reveal the effectiveness of the proposed approach and shows that it is possible to build a high accuracy model with less historical data using a combination of neural network and fuzzy logic which can be used in real time.

**Keywords:** Short term, load forecasting, Anfis, identification, modeling, time series analysis.

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## 1. INTRODUCTION

Various phenomenons are observed during regular time intervals and the resulting data can be used for different purposes. Short term electric load forecasting is one of the important criterions in the operation and planning of electrical power production. It concerns the prediction of power system loads over standard periods. The basic quantity of interest is usually the hourly total system load. It also concerned with the prediction of daily (short term), weekly and monthly values (medium term) of the system load and the maximum values occurred. However, much effort has been devoted over the past decades to develop and improve the short term electric load and its corresponding price forecasting models in order to make an appropriate market decision.

Based on their capabilities to approximate the nonlinear continuous function, to identify complex system and recognition, to predict time series...etc, neural network, evolutionary programming, fuzzy logic and neuro-fuzzy approaches have been successfully applied in several scientific and engineering fields in recent years. However, the

choice of the proper technique is important. In power system planning, several model based on neural network have been proposed for short term electric load forecasting, they enhanced their ability to learn and construct a highly nonlinear mapping throughout a set of input-output data pairs (Lee *et al*, 1992), (Chaturvedi *et al*, 2004). However, the work of Espinoza *et al* (Espinoza *et al*, 2007) focused on the application of nonlinear system identification technique for short term load forecasting. They used fixed-size least squares support vector machines for nonlinear estimation in NARX model. However, in the proposed model structure by Espinoza, the load at a given hour is predicted by the evolution of the load at previous hours. Their results confirm that, the forecasting performance assessed for different load series is satisfactory with a mean square error less than 3% on the test data.

Support vector machine techniques (SVM) for data classification and regression have been successfully applied to electric load prediction (Chen *et al*, 2004). Results obtained by Chen *et al*, shows that the climate information might not be useful in mid-term load forecasting. However, taking temperature factor into account may lead to imprecise

prediction since the temperature information requires the prediction of the future temperature which is very difficult. Nevertheless, model performances increase with an appropriate choice of data segments.

Artificial neural network model for short load forecasting provide errors when there are speedy fluctuations in load and temperature. To overcome difficulties and to have a good model, fuzzy adaptive inference and similarity which takes into account the effect of humidity and temperature have been employed (Amit *et al*, 2009). In this approach, fuzzy adaptive inference is employed to adjust the load curves on selected similar days and results obtained show a good prediction with a small mean absolute percentage error.

The power of hybrid system that use the advantage of neural networks and fuzzy logic have been also used to forecast medium and long term energy demand of a complicated electrical system (Zarghami *et al*, 2007). With the proposed approach, the authors try to search recurrent relationships in the historical data that allows the prediction of energy demand for several next years. In short term electric load forecasting, neuro-fuzzy technique has been employed for optimizing the prediction calculation (Yusra *et al*, 2007). Simulation results on a historical data of eighteen months give better prediction in comparison with conventional method. The drawback of this model is the use of a large number of historical data that is stretched in making decisions regarding the adjustment of production over consumption in real time.

The purpose of this paper is to analyze and discuss the short term load forecasting from different point of view. In our work, we propose a way of handling negative aspect of existing short term forecasting models as the use of many historical data and to reduce the learning time and complexity structure of neural networks classically used in electric load forecasting,

This paper is organized in four parts. In part 2 we recall the main objective and a description of load forecasting. Part 3 present a brief study of statistical and artificial intelligence methods used for load forecasting. Anfis structure will be presented in part 4. Results of proposed model structure for load forecasting of RTE weekly load consumption and discussion are showed in part 5 followed by a conclusion of our research.

## 2. DESCRIPTION AND OBJECTIVE OF LOAD FORECASTING

The main objective of load forecasting is to present the power load consumption for operation and planning. However, it help electric company producer to make decisions on purchasing, load switching, power generating, infrastructure development and for timely dispatcher information. Load forecasting play also an important role for contract evaluations of various financial products on energy pricing offered by the market. Moreover, load forecasting is a difficult task because of complexity, nonlinearity and many important exogenous variables that must be considered. For

the type of time load series under study, model development should take into account seasonal patterns.

Figure 1 presents the load curve for one week in January. It is found that the daily consumption usually begins with low values early in the morning followed by morning peak consumption. The power demand decreases significantly towards the end of the day. It shows also that the power demand on weekend is different from workdays. For a good prediction of the load series, building of a model must take into account variations in monthly and seasonal as well as the various factors affecting the load, such as weather fluctuations. However, the power consumed during one week in winter cold due to the increasing use of electric heaters differs from the power consumed during one week in summer warm which also increases due to the use of air conditioning equipment figure 1 and 2.

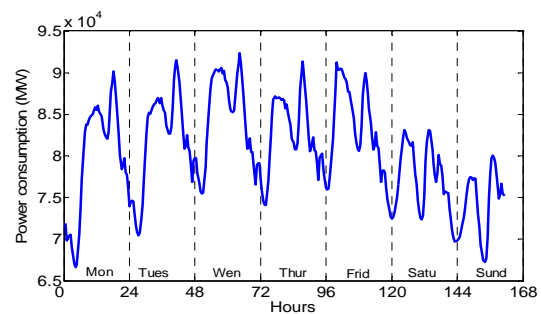


Fig. 1. Load series within a week (05 to 11 January 2009)

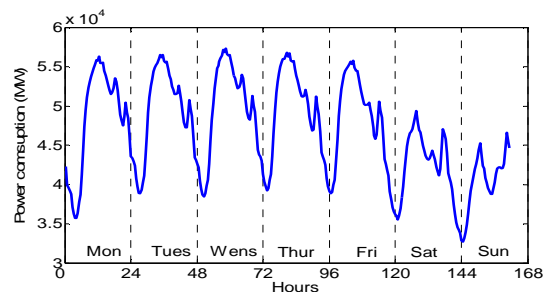


Fig. 2. Load series within a week (08 to 14 June 2009)

For different seasons, from figure 3 and 4 of the data under study, we can observe that the maximum power consumption occurs in winter seasons but the patterns of spring, summer and autumn are similar along the week except the first two days of the week.

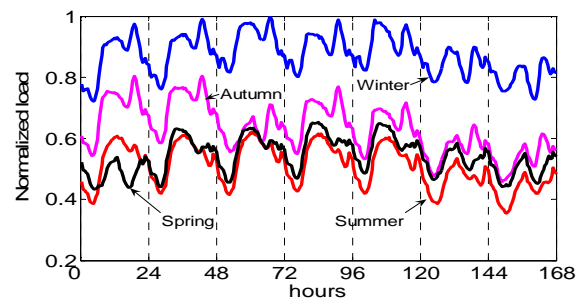


Fig. 3. Comparison of weekly sketch over the year

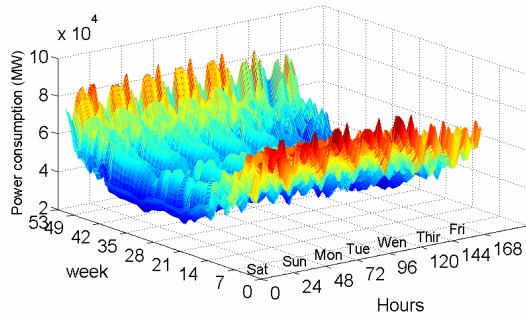


Fig. 4. Power consumption within a year

### 3. OVERVIEW OF LOAD FORECASTING METHODS

In the literature we can find a wide range of methods for electric load forecasting (Engle *et al*, 1992), (Ruzik *et al*, 2003), (Yang *et al*, 2001), (Azzam-ul-Asar *et al*, 2007). The classification is based on certain characteristics, such as the type of load model, the type of data to provide the model, the computational time required, the prediction algorithm and the availability of experimental results. Various methods and ideas have been tried for load forecasting, with varying degrees of success. They may be classified into two categories (Rafal, 2006), statistical and artificial intelligence.

#### 3.1 Statistical methods

Electricity load consumption is sampled 24 hours a day, 365 days a year. It represents a consecutive measurement taken at equally intervals what gives an opportunity to apply statistical methods including exponential smoothing (Cristianse *et al*, 1971), (Moghran *et al*, 1989), (El-Keib *et al*, 1995), (Taylor, 2003), time series (Amjady, 2001), (Chatfield, 2000) and regression methods (Papalexopoulos *et al*, 1990). These statistical techniques are attractive and allowing scientist to understand the system behavior under study. The drawback of these methods is their limit ability to model the nonlinearity of load consumption.

##### 3.1.1 Regression method

It is one of most widely used statistical techniques that reflect the relationship between power consumption and other factors such as time, date and type of consumption. The regression method tries to determine the current value using a mathematical combination of the previous loads and the exogenous factors, typically weather and social variables (Ruzic *et al*, 2003), (Charytoniuk *et al*, 1998). The objective of this method is usually to determine what the independent variables have the greatest influence on the dependent variable.

##### 3.1.2 Exponential smoothing

Used in a variety of applications because of its robustness and accuracy, in this approach, the prediction is constructed from an exponentially weighted average of past observations.

Further simplifications are required to accommodate the daily and the weekly in the electricity demand series for exponential smoothing of hourly data (Taylor *et al*, 2006).

##### 3.1.3 Similar-Day Method

In this approach, loads of similar day predict is considered as a linear or a regression procedure that can include several similar days (Yu-Jun He *et al*, 2005). Hence, it is based on searching historical data for days with similar characteristics to the forecasted day.

#### 3.2 Artificial intelligence based methods

Artificial intelligence methods tend to be flexible and can handle complexity and non-linearity,

##### 3.2.1 Expert system

These methods incorporate rules and procedures used by experts. Expert systems are heuristic models, which can usually take into account quantitative and qualitative factors in software which will then automatically be able to predict without human assistance. Several techniques were proposed since the 80s. A typical approach is to try to emulate the reasoning of a human operator. One possible method for creating a human expert prediction is to search the historical database on the day that best fits the target day, taking account of factors that characterize it. The values of the corresponding load recorded to date are then taken as the basis for forecasting (Ku-long Ho *et al*, 1990), (Rahman & hazim, 1996), (Rahman *et al*, 1988), (Hwan *et al*, 2001). An expert system can be an automated version of this kind of research process. Moreover, the expert system can refine its results taking more explicitly taking into account external factors and daily usage patterns.

##### 3.2.2 Neural network

Based on learning strategies, neural network methods for load forecasting can be classified into two groups. The first one is a supervised neural network that adjusts its weights according to the error between pre-tested and desired output. The second are methods based on unsupervised learning algorithm. Generally, methods based on supervised learning algorithm like a feed forward multilayer perceptron are used (Desouky *et al*, 2000), (Hippert *et al*, 2001).

##### 3.2.3 Fuzzy logic

Fuzzy logic is a generalization of Boolean logic; it allows deduction of output system from fuzzy imprecise inputs. However, model based on fuzzy logic are robust in forecasting because there are no need to mathematical formulation between system inputs and outputs Kim *et al*, 2000), (Mastorocostas *et al*, 1999), (Chow *et al*, 1997). Electrical load forecasting using fuzzy logic controller can use several factors as inputs like temperature and time. A defuzzification process is used to produce the desired output after processing logic inputs.

#### 4. Anfis structure

An adaptive Neuro-Fuzzy inference system is a cross between an artificial neural network and a fuzzy inference system. It is a fuzzy Takagi-Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation (Jang, 1993). The ANFIS architecture for two input variables  $x$  and  $y$  with two fuzzy sets  $A_1, A_2, B_1$  and  $B_2$  as is indicated in Figure.5.

In this architecture, the first layer is formed by adaptive nodes that give the degree of Fuzzy membership of the input. The second compute de firing strengths of the associated rules. Neurons constituting the third layer are fixed neurons and play a normalization role to the firing strengths from the previous layer. Fourth layer is adaptive who give the product of the normalized firing level and a first order polynomial. Finally, the last layer presents a summation of all incoming signals.

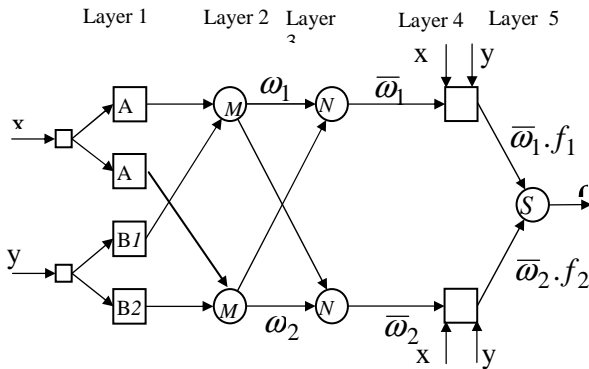


Fig. 5. ANFIS architecture

#### 5. PROPOSED FORECASTING MODEL STRUCTURE

Neuro-Fuzzy forecasting model has been tested firstly for modeling and forecasting weekly load. For model development of weekly time series data using ANFIS system, the time series data  $Z = \{Z_1, Z_2, \dots, Z_q\}$  has to be rearranged in a multi input single output.

For the given weekly data points modeling and forecasting the Neuro-Fuzzy predictor is supposed to work with ten inputs and one output only. The inputs are directly extracted from the data sets. Here, the weekly load data is used. There are 336 data samples  $(y(t), u(t))$ , from  $t=1$  to  $t=336$  corresponding of half hourly load for a week.

In order to predict weekly load consumption  $y(t)$ , we used ten dimensional vector as input described below:

Input =  $[y(t-1), y(t-2), y(t-3), y(t-4), u(t-1), u(t-2), u(t-3), u(t-4), u(t-5), u(t-6)]$ ;  
 Output= $[y(t)]$

To overcome the increased computational time and avoid the large number of rules and parameters of learning, we must select the input vectors according to the minimal error in the

first epochs of learning phase. In training phase, only the first 168 input-data sets are used whereas, remaining 168 data were used for prediction test represented by fig. 6. The presented data demonstrates that the training and checking data do not cover the same region.

The desired weekly load consumption and the Neuro-Fuzzy prediction were shown in fig 7. Results clearly show the excellent training as well as prediction performance of Takagi-Sugeno Neuro-Fuzzy network.

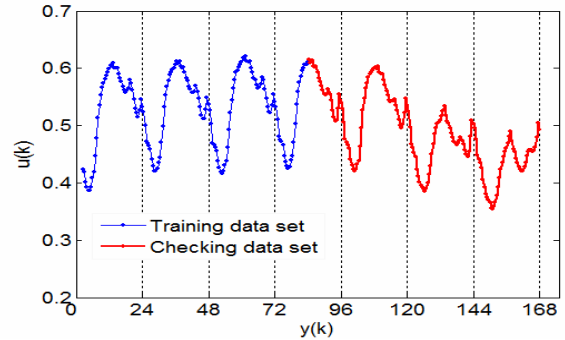


Fig. 6. Training and checking data for model building

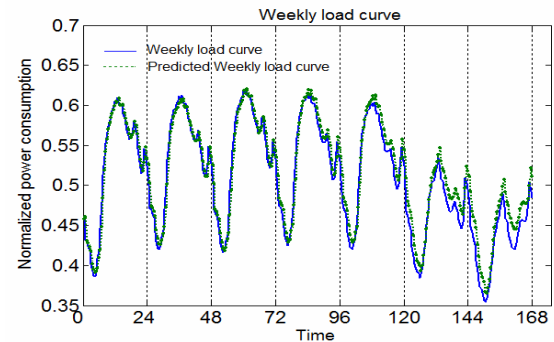


Fig. 7. Anfis output versus pre-tested output

The Neuro-Fuzzy structure used was programmed with computer. It uses 336 training data set in 1000 training epochs with arbitrary two membership functions to each variable chosen empirically by examining the desired input-output data. The rule number is 4, and the training and checking error are shown in fig 8.

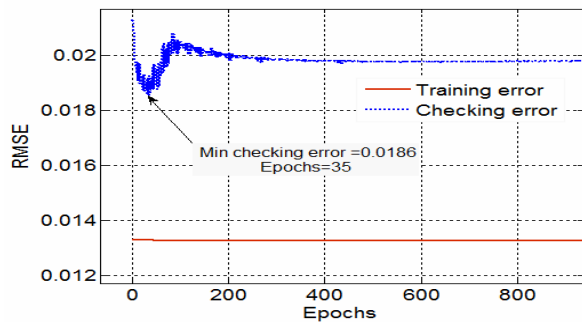


Fig. 8. Error curves

Figure.9 and figure 10 shows the initial and final membership functions using the generalized bell-shaped membership function.

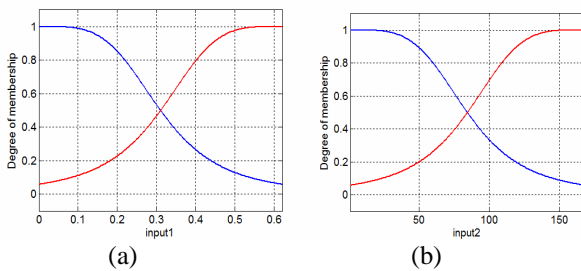


Fig. 9. Initial MF on x (a) and on y (b)

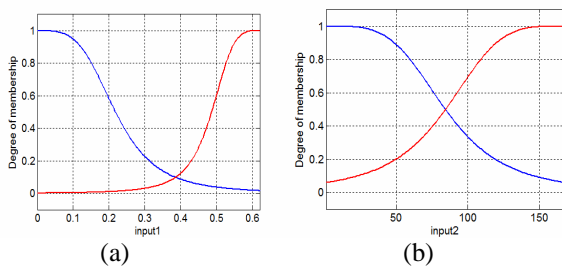


Fig. 10. Final MF on x (a) and on y (b)

## 6. CONCLUSIONS

In this study, application of neuro-fuzzy technique is presented for the prediction of the weekly load curve. ANFIS architecture is successfully used to predict power consumption. Results obtained are satisfactory and shows that the good accuracy of developed model is not affected by rapid fluctuations in power demand which is the main drawback of neural networks models. Hardware implementation of the proposed model can be done to have a real time system.

## REFERENCES

- Amit. Jain, E. Srinivas, R. Rauta (2009), Short Term Load Forecasting using Fuzzy Adaptive Inference and Similarity. *World congress on Nature & Biologically Inspired Computing (NaBIC 2009)*, Coimbatore India. pp 1743-1748.
- Amjady. N (2001), 'Short-term hourly load forecasting using time-series modeling with peak load estimation capability', *IEEE Transactions on Power Systems*, 2001, **v.16(3)**, 498 – 505.
- Azzam-ul-Asar; ul Hassnain, S.Riaz.; Affan Khan (2007), Short Term Load Forecasting Using Particle Swarm Optimization Based ANN Approach; *Neural Networks, 2007. IJCNN 2007. international Joint Conference on ; 12-17 Aug. 2007* Page(s):1476 – 1481.
- Chaturvedi, D. K, M. Mohan, R. K. Singh, and P. K. Kalra (2004). Improved generalized neuron model for short term load forecasting,. *International Journal on Soft Computing-A Fusion of Foundations, Methodologies and Applications. Springer-Verlag, Heidelberg*, **v. 8**, No. 1, pp. 10-18.
- Charytoniuk. W, M.S. Chen, P.Van Olinda, (1998), 'Nonparametric regression based short-term load forecasting', *IEEE Transactions on Power Systems*, **v. 13**, 725 – 730.
- Chen. Bo-Juen, Ming-Wei Chang, and Chih-Jen Lin. (2004). Load forecasting using support vector machines: A study on EUNITE competition 2001. *IEEE Transactions on Power Systems*. **v.19 N°04**, pp. 1821-1830.
- Chow. M and H. Tram, (1997), "Application of fuzzy logic technology for spatial load forecasting," *IEEE Trans. Power Syst.*, **v. 12, no. 3**, pp. 1360-1366.
- Christiansen. W, 'Short Term Load Forecasting Using General Exponential Smoothing', *IEEE Transactions on PAS*, 1971, 900 – 910.
- Chris Chatfield, (2000), *Time-series forecasting*, Chapman & Hall
- Desouky. A. A, M.M. Elkateb, (2000), 'Hybrid adaptive techniques for electric-load forecast using ANN and ARIMA', *IEE Proceedings of Generation, Transmission and Distribution*, 2000, **v. 147(4)**, 213 - 217.
- El-Keib, A.A.,Ma, X. andMa, H. (1995) Advancement of statistical based modeling for short-term load forecasting, *Electric Power Systems Research* **v.35**, 51–58.
- Engle. R. F, C. Mustafa, J. Rice (1992), 'Modeling peak electricity demand', *Journal of Forecasting*, **v.11**, pp 241 – 251.
- Espinoza. M, J.A.K. Suykens, R. Belmans and B. De Moor (2007), Electric load forecasting using Kernel-Based modelling for nonlinear system identification. *IEEE CONTROL SYSTEM MAGAZINE*. p. 43-57.
- Jang, J. S (1993), ANFIS: Adaptive-network-based fuzzy Inference Systems", *IEEE Transactions on Systems, Man and Cybernetics. Part B: Cybernetics*, **v. 23**, pp. 665-685.
- Hippert. H. S, C. E. Pedreira, and R. C. Souza, (2001), "Neural networks for short-term load forecasting: A review and evaluation," *IEEE Trans. Power Syst.*, **v. 6, no.1**, pp. 44–55.
- Hwan. K. J, G.W. Kim, (2001) 'A short-term load forecasting expert system', *Proceedings of The Fifth Russian-Korean International Symposium on Science and Technology*, pp.112 – 116.
- Kim, K. H, H.A.Youn, Y.C. Kang, (2000), 'Short-term load forecasting for special days in anomalous load conditions using neural networks and fuzzy inference method', *IEEE Transactions on Power Systems*, **v.15(2)**, 559 – 565.
- Ku-Long Ho. Yuan-Yih Hsu Chuan-Fu Chen Tzong-En Lee Chih-Chien Liang Tsau-Shin Lai Kung-Keng Chen (1990), 'Short-term load forecasting of Taiwan power system using a knowledge based expert system', *IEEE Transactions on Power Systems*, **v. 5**, pp.1214 – 1221.
- Lee. K. Y, Y. T. Chat, J. H. Park (1992). Short term load forecasting using an artificial neural network.

- Transactions on power systems*. **V.07**, N°01, pp 124-132.
- Mastorocostas. P. A, 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.*, **v.14**, **no. 1**, pp. 29-36.
- Moghran, I. and Rahman, S. (1989) Analysis and evaluation of five short-term load forecasting techniques, *IEEE Transactions on Power Systems* **v.4**, 1484–1491.
- Papalexopoulos A. D, T.C. Hesterberg (1990), ‘A Regression Based Approach to Short Term Load Forecasting’, *IEEE Transactions on Power Systems*, 1990, **5(1)**, 40 – 45.
- Rahman. S, O. Hazim, (1996), ‘Load forecasting for multiple sites: development of an expert system-based technique’, *Electric Power Systems Research*, **v.39**, 161 – 169.
- Rahman. S and R. Bhatnagar, (1988), “An expert system based algorithm for short term load forecast,” *IEEE Trans. Power Syst.*, **v. 3**, **no. 2**, pp. 392–399.
- Rafal. W (2006) Modeling and forecasting electricity loads and prices, a statistical approach. Jhon Wiley and Sons ltd.
- Ruzic. S, A. Vuckovic, N. Nikolic, (2003) ‘Weather sensitive method for short-term load forecasting in electric power utility of Serbia’, *IEEE Transactions on Power Systems*,**V.18**, pp.1581 – 1586.
- Taylor, J.W. (2003) Short-term electricity demand forecasting using double seasonal exponential smoothing, *Journal of Operational Research Society* **v. 54**, 799–805.
- Taylor, J.W., de Menezes, L. and McSharry, P.E. (2006) A comparison of univariate methods for forecasting electricity demand up to a day ahead, *International Journal of Forecasting* **v.22(1)**, 1–16.
- YanXi Yang; Gang Zheng; Ding Liu (2001), BP-GA mixed algorithms for short-term load forecasting; *Proceeding of International Conferences on Info-tech and Info-net*, 2001, **V.4. 29** oct-1 Nov 2001. pp. 334-339.
- Yusra. S, D. Hamdani, M. Bachtiar Nappu (2007), “Application of Adaptive Neuro-Fuzzy Method for Forecasting Short-Term Load Demand”, *Proceedings of the International Conference on Electrical Engineering and Informatics Institut Teknologi Bandung, Indonesia* June 17-19, 2007
- Yu-Jun He You-Chan Zhu Jian-Cheng Gu Cheng-Qun Yin (2005). ‘Similar Day Selecting Based Neural Network Model and its Application in Short-Term Load Forecasting’, *Machine Learning and Cybernetics Proceedings of 2005 International Conference*, 18 - 21 Aug. 2005, **v.8**, 4760 – 4763.
- Zargham H, F. Kavehnia, M. Askari, M. Ganbariyan (2007), “Time-Series Load Modelling and Load Forecasting Using Neuro-Fuzzy Techniques”, *9<sup>th</sup> International Conference Electrical Power Quality and Utilisation*, Barcelona 9-11 October 2007.