Research Inventy: International Journal of Engineering And Science
Vol.5, Issue 10 (October 2015), PP -08-12
Issn (e): 2278-4721, Issn (p):2319-6483, www.researchinventy.com

Electric Load Forecasting

[1] Mr. Ankush R. Sarode, [2] *Prof. Mukund R. Salodkar*
[1,2](Department of Electronics and Power,
G.H. Raisoni College of Engineering and Management, Amravati)

ABSTRACT - *Load forecasting is vitally important for the electric industry in the deregulated economy. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development. A large variety of mathematical methods have been developed for load forecasting. The present title discloses a novel approach for carrying out the constraints of energy requirements and minimizes the wastage of power at the workstations, mall, libraries, visiting centers, house hold requirements by actively predicting the power requirements.*
Keywords - *ANFIS, Energy Management, Fuzzy Logic, Load Forecasting*

I. INTRODUCTION

Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. Load forecasts are extremely important for energy suppliers, ISOs, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets. Load forecasts can be divided into three categories: short-term forecasts which are usually from one hour to one week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year. The forecasts for different time horizons are important for different operations within a utility. For example, for a particular region, it is possible to predict the next day load with an accuracy of approximately 1-3%. However, it is impossible to predict the next year peak load with the similar accuracy since accurate long-term weather forecasts are not available. For the next year peak forecast, it is possible to provide the probability distribution of the load based on historical weather observations. It is also possible, according to the industry practice, to predict the so-called weather normalized load, which would take place for average annual peak weather conditions or worse than average peak weather conditions for a given area. Weather normalized load is the load calculated for the so-called normal weather conditions which are the average of the weather characteristics for the peak historical loads over a certain period of time. The duration of this period varies from one utility to another. Most companies take the last 25-30 years of data.

Load forecasting has always been important for planning and operational decision conducted by utility companies. However, with the deregulation of the energy industries, load forecasting is even more important. With supply and demand fluctuating and the changes of weather conditions and energy prices increasing by a factor of ten or more during peak situations, load forecasting is vitally important for utilities. Short-term load forecasting can help to estimate load flows and to make decisions that can prevent overloading. Timely implementations of such decisions lead to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts. Load forecasting is also important for contract evaluations and evaluations of various sophisticated financial products on energy pricing offered by the market. In the deregulated economy, decisions on capital expenditures based on long-term forecasting are also more important than in a non-deregulated economy when rate increases could be justified by capital expenditure projects.
The Electric Load Forecasting System is proposed around ANFIS system- is a kind of artificial Neural Network which is based on inference system. As it integrates benefits of both neural network and fuzzy logic principles it has potential to capture the benefits of both technologies in a single framework.

II. FACTORS AFFECTING THE FORECAST:

For short-term load forecasting several factors should be considered, such as time factors, weather data, and possible customers' classes. The medium- and long-term forecasts take into account the historical load and weather data, the number of customers in different categories, the appliances in the area and their characteristics including age, the economic and demographic data and their forecasts, the appliance sales data, and other factors. The time factors include the time of the year, the day of the week, and the hour of the day. There are important differences in load between weekdays and weekends. The load on different weekdays also can behave differently. For example, Mondays and Fridays being adjacent to weekends, may have structurally different loads than Tuesday through Thursday. This is particularly true during the summer time. Holidays are more difficult to forecast than non-holidays because of their relative infrequent occurrence. Weather conditions influence the load. In fact, forecasted weather parameters are the most important factors in short-term load forecasts. Various weather variables could be considered for load forecasting. Temperature and humidity are the most commonly used load predictors.

III. FORECASTING METHODOLOGIES:

As the forecasting methodologies are procedures for quantitatively defining future loads. It can be classified depending on time period:

a. Short Term
b. Intermediate
c. Long Term

The short term plotting is carried out on daily load basis, also called Daily Load Curve, intermediate is carried out on monthly basis also called as monthly load curve and long term is carried out on annual basis also called as annual load curves, when plotted using load curves techniques.

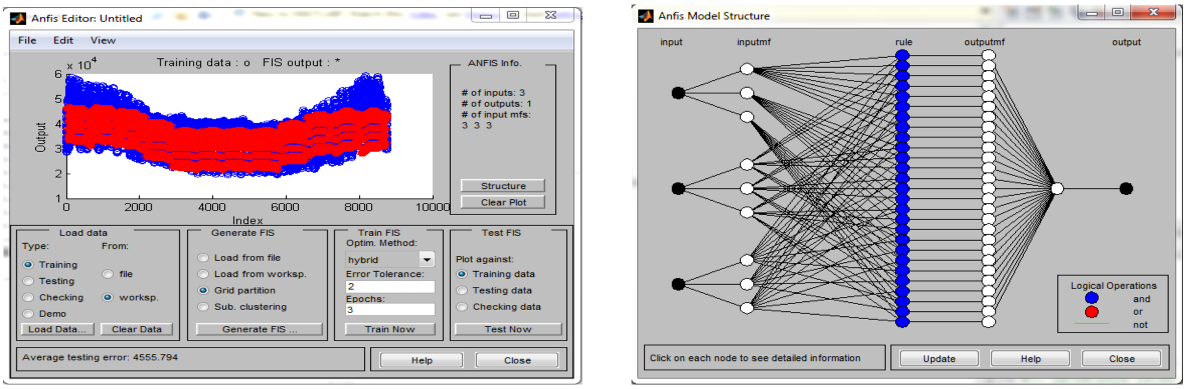

Fig 1: ANFIS Structure

IV. IMPLEMENTATION TECHNIQUES

Effective forecasting techniques can be implemented using different platform: Embedded System, Using Programmable Devices and Using Neuro-Fuzzy System.

Considering the different shortcomings of the other two platforms the present novel concept is implemented using Artificial Neural Network- ANFIS Technique.

ANFIS is meant for integrating features if Fuzzy System and Neural Network. From Fuzzy System: it is representation of prior Knowledge into set of constraints (Network Topology) to reduce the optimization search space.

And from Neural Network: It is adaptation of back propagation to structured network to automate Fuzzy control parametric tuning.

In the present title, short term forecasting is executed. i.e. the network is designed for predicting the next hour expected load. Which can be procured and fulfilled from the power station well in advanced.

For designing the network, three inputs are considered viz: Hour, date and month. This statistics of the pattern recorded for particular location is given as membership function inputs to the network for training.

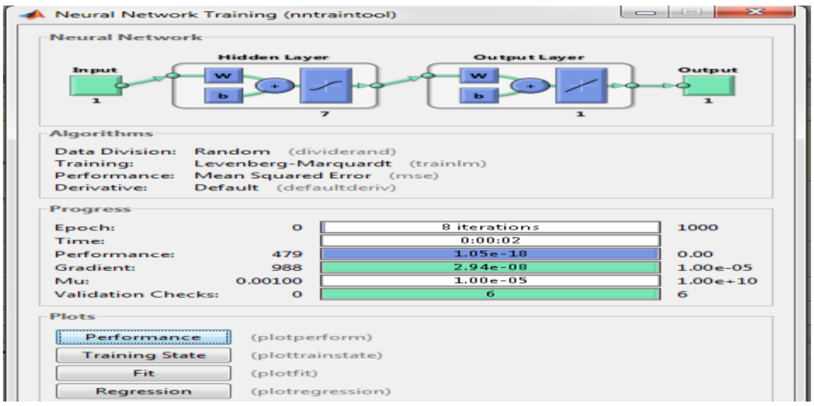

Fig.2: Neural Network Training

Hour, date and month patterns are given as input will be then recorded and membership functions are created which nothing but the implementation is of if part.
In the input column "H" indicates Hour Input, "D" indicates Date Input and "M" indicates Month input to the ANFIS Network.

Based on the conditions i.e. if part certain rules are defined. Like number of membership functions to be implemented and their inter-relations. Once the membership functions are defined and rules are defined then the network is ready to use. That means it is in the state of predicting the load pattern to be fulfilled.

The first step is executed by the fuzzifier which converts the input data pattern in to fuzzy sets. These set of data patters in now the exact input to the ANFIS system. Second crucial stage is executed by the permutator which applies all the possible combinations to the fuzzy set. This comes under the Rules + Norm Section. And the final, most decisive stage of the proposed system is inference unit. In the proposed system, the intermediate data generated is multiplied with the correcting factor of 1.2 units.

The title proposes 1.2 multiplication factor as the best suitable unit for predicting the most precise forecasting. This multiplication factor depends on different parameters like Location, Weather conditions, days of the year and etc. Based on the experiment conducted for this title, 1.2 multiplication factor which is also called as the Bias of the system is best suitable.

The inference unit is basically implementing the then part of the above figure.
The unit is designed and trained which has then certain set of output pattern data, also called as the Permutator unit.

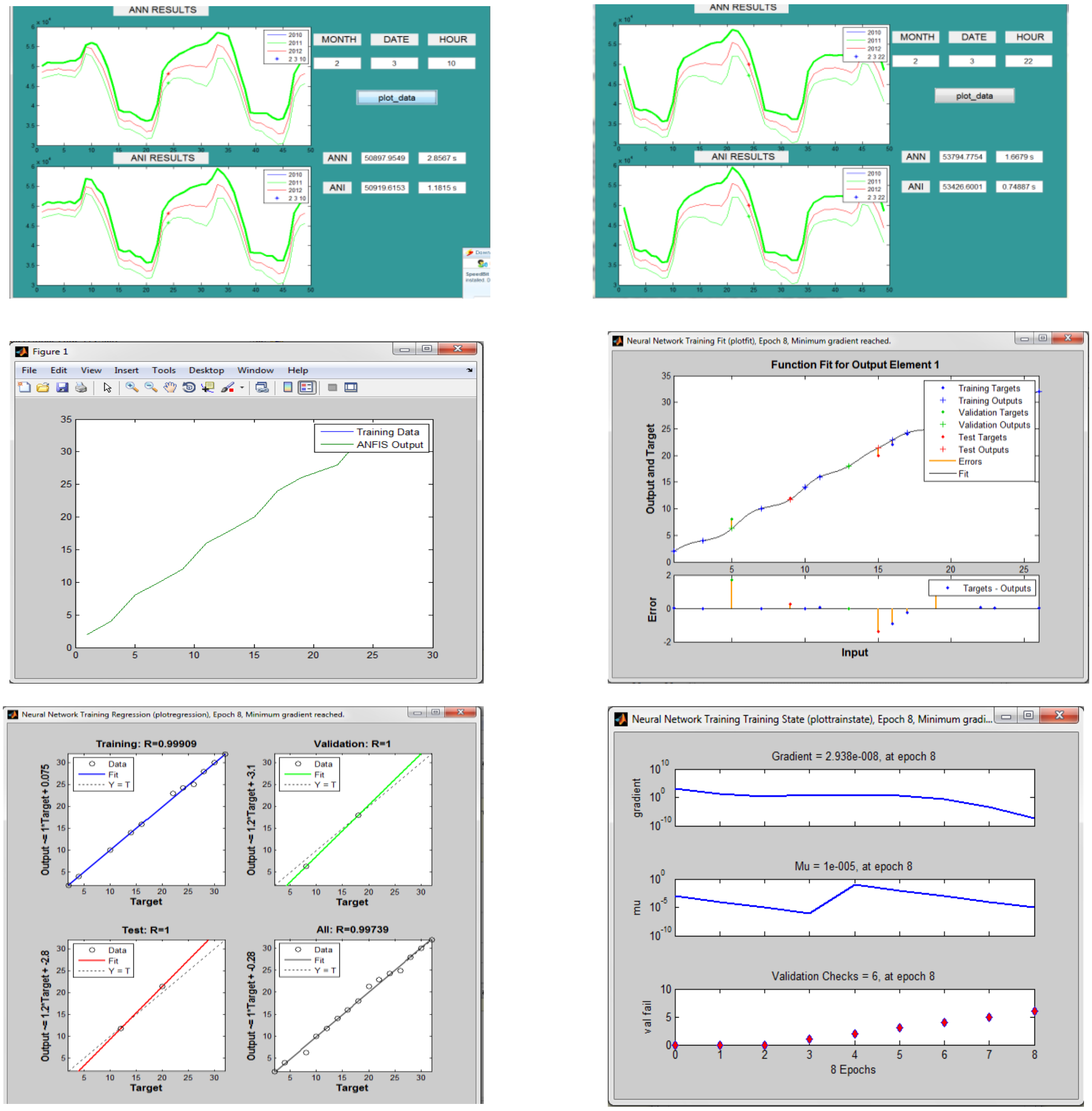

Fig. 3: Sample Result Generated

Figure 3 shows the sample result generated for the three input i.e. hour, date and month. The input data is given for 12:00 A.M. to 12:00 A.M. as a day input, 1 to 30 as date input and 1 to 12 as month input to the proposed ANFIS network.

The proposed system is not only suitable for implementing the Load forecasting of the Power Generation Unit but is also suitable for implementing stock exchange system. In this system the historical values are given as an input to the Forecasting System with which it is possible to forecast sensex values.

Second applications is in medical science in which again certain pre-coded data values which specifies the symptoms of the disease like cancer, heart attaché and diabetes. In this mode of the system it is possible to take corrective actions for the patient before the serious health mode.

In the third mode of the application of the system, weather forecasting can also be implemented for uncertain areas. The proposed system again can be implemented in three different ways for short term forecasting, intermediate and long term forecasting. But the proposed system is best suitable for weather forecasting if it is implemented considering Short Term Forecasting. Since, for the sites where the environment changes all of sudden, makes the system failure when implemented in intermediate and long term basis.

For implementation of the above three systems ANFIS network can be modified in terms of number of inputs, intermediate membership functions and number of outputs to implement the desired system.

V. PROPOSED MODIFICATIONS:

It is possible to extend the boundaries of applicability of the developed models and algorithms. So far, there is no single model or algorithm that is superior for all utilities. The reason is that utility service areas vary in differing mixtures of industrial, commercial, and residential customers. They also vary in geographic, climatologic, economic, and social characteristics. Selecting the most suitable algorithm by a utility can be done by testing the algorithms on real data. In fact, some utility companies use several load forecasting methods in parallel. Nothing is known on a priori conditions that could detect which forecasting method is more suitable for a given load area. But yes it is important to investigate the sensitivity of the load forecasting algorithms and models to the number of customers, characteristics of the area, energy prices, and other factors.

VI. CONCLUSIONS:

Accurate load forecasting is very important for electric utilities in a competitive environment created by the electric industry deregulation. In this paper, some statistical and artificial intelligence techniques that are used for electric load forecasting are discussed, also discussed factors that affect the accuracy of the forecasts such as weather data, time factors, customer classes, as well as economic and end use factors. Load forecasting methods use advanced mathematical modelling. Additional progress in load forecasting and its use in industrial applications can be achieved by providing short-term load forecasts in the form of probability distributions rather than the forecasted numbers; for example the so-called ensemble approach can be used.

The progress in load forecasting will be achieved in two directions: (i) basic research in statistics and artificial intelligence and (ii) better understanding of the load dynamics and its statistical properties to implement appropriate models.

REFERENCES:

[1] A. G. Bakirtzis, V. Petridis, S. J. Kiartzis, M.C. Alexiadis, and A.H. Maissis. A Neural Network Short-Term Load Forecasting Model for the Greek Power System. IEEE Transactions on Power Systems, 11:858–863, 1996.

[2] B.J. Chen, M.W. Chang, and C.J. Lin. Load Forecasting using Support Vector Machines: A Study on EUNITE Competition 2001. Technical report, Department of Computer Science and Information Engineering, National Taiwan University, 2002.

[3] W. Charytoniuk, M. S. Chen, and P. Van O linda. Nonparametric Regression Based Short-Term Load Forecasting. IEEE Transactions on Power Systems, 13:725–730, 1998. [4] H. Chen, C.A. Canizares, and A. Singh. ANN-Based Short-Term Load Forecasting in Electricity Markets. Proceedings of the IEEE Power Engineering Society Transmission and Distribution Conference, 2:411–415, 2001.

[4] M. Y. Cho, J.C. Hwang, and C.S. Chen. Customer Short-Term Load Forecasting by using ARIMA Transfer Function Model. Proceedings of the International Conference on Energy Management and Power Delivery, 1:317–322, 1995.

[5] N. Christiani and J. S. Taylor. An Itroduction to Support Vector Machines and Other Kernel-Based Learning Methods. Cambridge University Press, Cambridge, 2000.

[6] T.W.S. Chow and C.T. Leung. Nonlinear Autoregressive Integrated Neural Network Model for Short-Term Load Forecasting. IEE Proceedings on Generation, Transmission and Distribution, 143:500– 506, 1996.

[7] J. Dudhia and J.F. Bresch. A Global Version of the PSU-NCAR Mesoscale Model. Monthly Weather Review, 130:2989–3007, 2002.

[8] S.E. Skarman and M. Georgiopoulous. Short-Term Electrical Load Forecasting using a Fuzzy ARTMAP Neural Network. Proceedings of SPIE, 181–191, 1998.

[9] R.F. Engle, C. Mustafa, and J. Rice. Modeling Peak Electricity Demand. Journal of Forecasting, 11:241–251, 1992.

[10] J.Y. Fan and J.D. McDonald. A Real-Time Implementation of Short-Term Load Forecasting for Distribution Power Systems. IEEE Transactions on Power Systems, 9:988–994, 1994.

[11] E.A. Feinberg, J.T. Hajagos, and D. Genethliou. Load Pocket Modeling. Proceedings of the 2nd IASTED International Conference: Power and Energy Systems, 50–54, Crete, 2002.

[12] E.A. Feinberg, J.T. Hajagos, and D. Genethliou. Statistical Load Modeling. Proceedings of the 7th IASTED International MultiConference: Power and Energy Systems, 88–91, Palm Springs, CA, 2003.
[13] E.A. Feinberg, J.T. Hajagos, B.G. Irrgang, R.J. Rossin, D. Genethliou and D.E. Feinberg. Load pocket forecasting software. Submitted to IASTED Journal on Energy and Power Systems.
[14] D.B. Fogel. An Introduction to Simulated Evolutionary Optimization. IEEE Transactions on Neural Networks, 5:3–14, 1994.
[15] C.W. Gellings. Demand Forecasting for Electric Utilities. The Fairmont Press, Lilburn, GA, 1996.
[16] T. Haida and S. Muto. Regression Based Peak Load Forecasting using a Transformation Technique. IEEE Transactions on Power Systems, 9:1788–1794, 1994.
[17] H.S. Hippert, C.E. Pedreira, and R.C. Souza. Neural Networks for Short-Term Load Forecasting: A Review and Evaluation. IEEE Transactions on Power Systems, 16:44–55, 2001.
[18] "Short term load forecasting using fuzzy neural networks", IEEE Transactions on Power Systems, Vol.10, No.3 August 1995.
[19] "Short term load forecasting for special days in anomalous load conditions using ANN", IEEE Transactions on Power Systems, Vol.15, No.1 February 2001.
[20] "One hour ahead load forecasting using neural networks", IEEE Transactions on Power Systems, Vol.17, No.1, February 2002.
[21] "Load forecasting using support vector machines: A study on EUNITE competition 2001", IEEE Transactions on Power Systems, Vol.19, No.4, November 2004.
[22] "Composite modeling for adaptive short term load forecasting", IEEE Transactions on Power Systems, Vol.6, No.2, May 1991.
[23] "Comparison tests of fourteen distribution load forecasting methods", IEEE Transactions on Power Systems, Vol.PAS-103, No.6, June 1984.
[24] "Automated load forecasting", IEEE Transactions on Power Systems, Vol.3, No.3, August 1988.
[25] "Regressive based peak load forecasting using transformation technique", IEEE Transactions on Power Systems, Vol.19, No.4 November 1994.
[26] "Short term load forecasting for fast developing utility using knowledge-based expert systems", IEEE Transactions on Power Systems, Vol.17, No.4, May 2002.
[27] "Quantitative forecasting-The state of the explorative models", j.opl.Res.Soc. Vol 30, No.8, 1979.
[28] "Short term load forecasting", IEEE Transactions on Power Systems, Vol.75, No.12, pp. 1558-1973, December 1987.
[29] "Comparative models for electrical load forecasting", John Wiley and Sons Ltd. 1985.
[30] "Short term peak demand forecasting in fast developing utility with inherent dynamic load characteristics", IEEE Transactions on Power Systems, Vol.5, No.3, August 1990. pp. 813-824.
[31] "Short term power system load forecasting using the iteratively reweighed least squares algorithm", Electric power system research, 19(1990) pp.11-12.
[32] O. Hyde and P.F. Hodnett. An Adaptable Automated Procedure for Short-Term Electricity Load Forecasting. IEEE Transactions on Power Systems, 12:84–93, 1997.
[33] A. Khotanzad, R.A. Rohani, T.L. Lu, A. Abaye, M. Davis, and D.J. Maratukulam. ANNSTLF–A Neural-Network-Based Electric Load Forecasting System. IEEE Transactions on Neural Networks, 8:835–846, 1997.
[34] A. Khotanzad, R.A. Rohani, and D. Maratukulam. ANNSTLF– Artificial Neural Network Short-Term Load Forecaster– Generation Three. IEEE Transactions on Neural Networks, 13:1413–1422, 1998.
[35] S.J. Kiartzis and A.G. Bakirtzis. A Fuzzy Expert System for Peak Load Forecasting: Application to the Greek Power System. Proceedings of the 10th Mediterranean Electrotechnical Conference, 3:1097– 1100, 2000.
[36] Y. Li and T. Fang. Wavelet and Support Vector Machines for Short-Term Electrical Load Forecasting. Proceedings of International Conference on Wavelet Analysis and its Applications, 1:399– 404, 2003.
[37] V. Miranda and C. Monteiro. Fuzzy Inference in Spatial Load Forecasting. Proceedings of IEEE Power Engineering Winter Meeting, 2:1063–1068, 2000.
[38] M. Mohandes. Support Vector Machines for Short-Term Electrical Load Forecasting. International Journal of Energy Research, 26:335–345, 2002.
[39] H. Mori and N. Kosemura. Optimal Regression Tree Based Rule Discovery for Short-Term Load Forecasting. Proceedings of IEEE Power Engineering Society Transmission and Distribution Conference, 2:421–426, 2001.
[40] A.D. Papalexopoulos, S. Hao, and T.M. Peng. An Implementation of a Neural Network Based Load Forecasting Model for the EMS. IEEE Transactions on Power Systems, 9:1956–1962, 1994.
[41] M. Peng, N.F. Hubele, and G.G. Karady. Advancement in the Application of Neural Networks for Short-Term Load Forecasting. IEEE Transactions on Power Systems, 7:250–257, 1992.
[42] S. Rahman. Formulation and Analysis of a Rule-Based Short-Term Load Forecasting Algorithm. Proceedings of the IEEE, 78:805–816, 1990. REFERENCES 285.
[43] S. Rahman and O. Hazim. Load Forecasting for Multiple Sites: Development of an Expert System-Based Technique. Electric Power Systems Research, 39:161–169, 1996.
[44] S. Ruzic, A. Vuckovic, and N. Nikolic. Weather Sensitive Method for Short-Term Load Forecasting in Electric Power Utility of Serbia. IEEE Transactions on Power Systems, 18:1581–1586, 2003.

Author Information:

Mr. Ankush R. Sarode is currently working as Lecturer with Department of Electrical Engineering at Brahmdeo Dada Mane Polytechnic Solapur since 2013. He is Persuing his M.E. in Electrical Power System from G. H. Raisoni College of Engineering and Management, Anjangaon Bari Road, Amravati. His areas of interest are Fuzzy Based System Design, Artificial Neural Network, and Digital System Design.

Prof. M. R. Salodkar is currently working as Head of the Department for Electrical Power System Engineering at G. H. Raisoni College of Engineering and Management, Anjangaon Bari Road, Amravati. His areas of interest are Power System and Transmission Lines.