Proceedings of the 2006 IASME/WSEAS International Conference on Energy & Environmental Systems, Chalkida, Greece, May 8-10, 2006 (pp299-304)

A Neuro-fuzzy Approach to Forecast the Electricity Demand

CAMELIA UCENIC
Department of Management and Industrial Systems
Technical University of Cluj Napoca
Address: Muncii Boulevard 103-105
ROMANIA

ATSALAKIS GEORGE
Department of Production Engineering and Management
Technical University of Crete
GREECE

Abstract: - This work presents a neuro-fuzzy model for solving the medium – term electric load-forecasting. The model used a time series of monthly data. The load forecasting is based on Adaptive Neural Fuzzy Inference System (ANFIS). The results are compared to those of an Autoregressive (AR) model and an Autoregressive Moving Average model (ARMA). The ANFIS model gave better results than AR and ARMA model.

Key-Words: - ANFIS, AR, ARMA, electricity demand, forecasting

1 Introduction

The energy sector is characterized by the presence of monopoly almost in all countries. The companies which act in this field are owned or regulated by government. As a commodity, electricity has some special characteristics in comparison with other types of commodities. The main one is that it can't be stored. It is consumed as it is generated and is very often sold in advance of production. Limitation of energy resources in addition to environmental factors requires the electric energy to be used more efficiently and more efficient power plants and transmission lines to be constructed. It is very important to forecast correctly the electricity demand.

The electricity market is changing quickly. The trend is for an international movement toward competitiveness combined with a more flexible and efficient electricity industry. The idea is to supply cheaper electricity for entire community. Some countries like USA, UK, and Japan have been supplied electricity by a large number of regional generators and created mechanisms to allow some form of trade between them. [1] Another aspect is the increased renewable energy sources.

To forecast the load is an important part of energy management system. The forecasting is done for short-run or for medium and long-run. Forecast error in load predictions results in increased operation costs.

In short term load forecasting (STLF) intends to predict electric load for a time period equaled with minutes, hours, days or weeks. It is important for the real time control of energetic systems. A prediction for a period 1-24 hours is used for unit commitment, energy transfer scheduling and load dispatch. The weight of short run load forecast is bigger in isolated power grids with increased renewable energy sources penetration. [15]

The short-term forecast is needed for control and scheduling of power system, and also as inputs to load flow study or contingency analysis. It is important in the daily operation of a power utility. To have an accurate, fast and robust forecasting methodology is of importance to the electric utility and also for consumers.

In long run, the load is an evolving variable. Unlike STLF, LTLF is affected by economical factors rather than weather conditions, like GDP, GNP, index of industrial production, oil price, energy consumption, electricity price. The electric demand increased a lot as a result of the increasing economic activity over the last years. To determine and quantify correctly the rate of increase gives the real shape of the load.

The electrical demand has special cycles. The cycles in the load occur at weakly and yearly time scale. Daily load data can be disaggregated into distinct groups called day-types. Each of them has common characteristics. Is a difference between the shape of the load on Sunday and Monday due to decreased economic activity on Sunday. Another difference is between the shape of a winter day and summer day. The first one exhibits a higher peak to the second one due to increased lighting needs in winter. The existence of several different day-types has been shown by several researchers. The level of desegregation in day-type selection is subjective and dependant on the judgement of the forecaster.

As pointed out by Hubele and Cheng in "Identification of seasonal short-term forecasting models using statistical decision functions", the application of a separate load forecasting model for different seasons has the advantage that the models don't need to incorporate seasonal information. Further desegregation of the load by day of the week reduces further the amount of information that the model need incorporate. Where a single model is used for all the data, the day-type information is often incorporated as an additional input or the day-types must be identified. [8]

In order to predict the capacity of generation, transmission and distribution system, the type of facilities required in transmission expansion planning, annual hydro and terminal maintenance scheduling are necessary medium and long run forecasts.

On the other hand the load demand is affected also by the weather conditions: temperature, humidity. For example in Japan, at peak period, 1^0 C increases in temperature causes about 4500 MW increase in demand for electricity. Unfortunate the inaccuracy of weather forecasts limited the utilisation of load-weather models.

2 Related Research

There are many researchers who tried to make the forecasting of load and a lot of techniques were proposed. Load models are divided into three groups: non-weather sensitive models that depend on previous values of the load; weather-sensitive models that depend on weather variables; hybrid models.

Among the traditional techniques are: the Box and Jenkins method, Kalman filtering, AR (autoregressive) model. The regression models analyze the relation between load and the influence factors. Their disadvantage is that need heavy computational efforts.

Time series models use extrapolation of historical data for the estimation of future hourly loads. The weak point in these models is that the load trend is considered as stationary. In addition the other factors that influenced the load can't be taken into account. All types of time series models, as AR, MA, ARMA, ARIMA are of the non-weather sensitive models.

In last time the evolution of soft computing (SC) gave new possibilities for the researchers. Soft computing represents a new methodology to solve the problems. It gives solutions despite that the analyzed situations present a high level of uncertainty. When one referes to the SC, we understand generaly that it includes: neuro-networks, fuzzy inference systems, genetic algorithms and a set of derivative free optimization techniques. These models are able to deal with tolerance for imprecision and uncertainty in time that conventional AI models deal only with precision and certainty.

The main characteristics of SC are: the human expertise, the biologically inspired computing models, the new optimization techniques, the numerical computation, the new application domains, the goal driven characteristics, the real world applications.

The neural based forecasting techniques can be classified into two categories, acording with the techniques they employ. First aproach considers the load pattern as a time series signal and predicts the future load by using the mentionated techniques. The second approach , load pattern is considered to be dependent both on previous load pattern and weather variables (temperature, wind speed, cloud cover, relative humidity).

The NN models differ from the usual time-series models. They include loads for both previous times and previous days and represent better the hourly variation than other existing methods.

a. Damien Fay in the paper *"Establishing a Solution Strategy for Electrical Demand Forecasting in Ireland"* described a preliminary analysis of Irish electrical load data. It presents the correlation between load and temperature taking into account the day, the season, the shape of the load curve. After, the authors established a general strategy to model the data in the view of these characteristics. The data were taken from two sources: the Electricity Supply Board (ESB) supply load data and the Meteorological Office of Ireland.

The data had a trend that increases at an increasing rate. In addition to the load trend there was used a growing variability v. In the next step different day-types were identified within the load data. The relationship between temperature and load within each day-type is of prime importance in modelling that day-type.

The forecast horizon that is the objective of research is three days. The consequences of applying a different model to each day-type was to reduce complexity in that the shape of the load in each day-type is consistent, but the data is more segmented, resulting several smaller data sets.

b. Another short term forecast for load demand was done in Australia- Victoria by Ajith Abraham in the paper *"A neuro-fuzzy approach for modelling electricity demand in Victoria"*. He used two popular SC techniques and ARIMA model. The methods considered are an evolving fuzzy neural network EFuNN and an artificial neural network ANN trained using scaled conjugate gradient algorithm and backpropagation algorithm.

The data were recorded half-hourly for a ten months period. The descriptor variables for network training are: minimum and maximum recorded temperatures, previous day's demand, season, day of the week and a value expressing the 0.5h period of the day. The network was trained only with 20% of the data

The results shown that EFuNN gave better results than other techniques in term of low RMSE error and less performance time. The disadvantage is that the determination of the network parameters (membership function, learning rates, and error thresholds) is complicated when we have a big number of inputs.

c. In order to decrease the weaknesses of NFS- the reduced number of inputs and the poor capacity to create their own structure, some researchers from Brazil proposed a Hierarchical Neuro-Fuzzy system based on the Binary Space Partitioning BSP. Its results are presented in the article *"The Hierarchical Neuro-Fuzzy BSP Model: An Application in Electric Load Forecasting"*.

The model uses monthly historical data of six utilities of the Brazilian electrical energy sector, between January 1983 and august 1998. The Theil's U coefficients obtained show the good quality of the forecast. The HNFB model always performed better than the Holt-Winters, Box&Jenkins and Backpropagation models with regard to the MAPE. For the RMSE metric, the HNFB performed better in most cases.

d. K. Kalaitzakis made a short-term load forecasting for isolated power systems (island of Crete) – *"Short-term load forecasting based on artificial neural networks parallel implementation"*. The paper proposed and compared several approaches like: Gaussian encoding GE, backpropagation BP, window random activation, radial basis function networks, real-time recurrent neural networks.

The methods are applied for 1-ahead prediction of the hourly electric load. The forecasting error statistical results of the minimum and maximum load time series, show that the proposed model provide better results compared to conventional autoregressive and BP forecasting models.

e. The same subject was treated by V.S. Kodogiannis [17]. Several neural architectures were tested including multilayer perceptrons, fuzzy-neural-type networks, radial basis and memory neuron networks. The building block of the forecasting system is a MLP trained with BP algorithm. Were applied two approaches to processing inputs in the time domain.

The performances are evaluated using metered data provided by the Greek Public Power Corporation. The results indicate that the load forecast is more accurate compared with conventional BP network forecasting models.

f. A forecasting of the power load for 1997 for the Wichita, Kansas was done by M. Tamimi and R. Egbert. They used a fuzzy-logic expert system integrated with Artificial Neural Network for a short time forecast.

The FL module maps the highly nonlinear relationship between the weather parameters and their impact on the daily electric load peak. The ANN module performs the task of learning the highly nonlinear input-output mapping directly from the training data.

The model forecasted the load demand for the next day with relatively low error. The maximum and minimum error during the summer was higher than the rest of the year due to the higher complexity of the weather-load relationship compared with spring and winter periods. In general, the maximum and minimum errors, the MAPE and SD results were favorable to the new FL-ANN model.

g. P.K. Dash [7] studied a self-organizing FNN that combines the self-organizing capability of NN with fuzzy-logic reasoning attributes. The network modeling starts with a random set of weights, and hence an arbitrary set of fuzzy sets. The proposed algorithm exploits the notion of error back-propagation. The network is initialized with random weights.

The system accounts for seasonal and daily characteristics as well as abnormal conditions, holiday or other. It is capable of forecasting load with a lead time of one day to one week. The weekly MAPE value gives that the model has a very good result in comparison with those obtained by BP neural networks.

h. A.K. Topalli [21] created a NN in order to forecast the total electric demand of Turkey. Getting unrealistic results couldn't be acceptable for a real time operation. Available past data is used off-line and the model is prepared for on-line data. A separate NN for each hour of the day is taken. To forecast the load one-day in advance for a specific hour, the load from present day and from two previous days are used to investigate the influences.

The weights are randomized. The inputs from data set are presented randomly and the output is obtained. Weights are updated in accordance with the error by a predetermined number of cycles. It is called off-line learning. In the on-line learning phase, the load values for the next year are tried to be forecast. The model reduces convergence time of on-line learning since the weights are already brought near to optimal values before this learning starts.

i. A hybrid model was used [2] to forecast the short-term load in Canada. The model utilizes moving window of current values of weather data as well as recent past history of load and weather data. The load forecasting is based on state space and Kalman filter approach.

The results were presented and compared with results based on least squares techniques. The model produces better and accurate results compared to those obtained earlier.

j. An improved NN approach based on a combined unsupervised /supervised learning concept was proposed for short-term load forecast in Serbia [7]. The unsupervised learning UL is used to identify days with similar daily load patterns. A feed-forward three-layer NN predict 24-hours load within the supervised learning phase.

The method is characterizes by a self-revision and adaptation capability. “Moving window” procedure applied in the process of creating training set data and re-training for each forecast day allows incorporating of possible different customer responses to most recent changes in factors.

The effectiveness is demonstrated by comparison of forecasted hourly loads in every day in 1991 with data realized in the same period in the Electric Power Utility of Serbia.

k. Regarding a long-term load forecasting, a study was done for prediction of peak electric load, using ANN. The feed-forward and feed-backward methods were considered to be proper. LTLF is affected by economical factors rather than weather conditions. Ten input factors are taken into consideration: GNP, GDP, population, number of households, number of air-conditioners, amount of CO_2 pollution, index of industrial production, oil price, amount of energy consumption and electricity price.

It has been demonstrated that the proposed BP and RNN give relatively accurate load forecasts for the actual data. Generally, 10% forecasting error is said to be acceptable for long-term load forecasting. The model gave only 3% error.

3 Model Presentation

An ANFIS model was used to predict the monthly load and an one step ahead prediction was choosen. The model belongs to non-whether forecasting models.

A neuro-fuzzy system is defined as a combination of Artificial Neural Networks (ANN) and Fuzzy Inference System (FIS) in such a way that neural network learning algorithm are used to determine the parameters of FIS [6]. Adaptive Neural Fuzzy Inference System (ANFIS) is a system that belongs to neuro-fuzzy category.

Functionally, there are almost no constraints on the node functions of an adaptive network except piecewise differentiability. Structurally, the only limitation of network configuration is that it should be of feedforward type. Due to this minimal restriction, the adaptive network's applications are immediate and immense in various areas.

Many tests were done in order to find the type of membership function that describe better the model. Finally two-membership functions of bell shape were chosen. The number of rules is two.

The type of ANFIS is Sugeno, the add method is the product, the or method is the max, the defuzzification method is the weight average, the implication method is the product and the aggregation method is the max. The number of nodes is 12, the number of linear parameters is 6, the number of non-linear parameters is 4, and so total parameters are 10.

The model uses a hybrid-learning algorithm to identify the parameters for the Sugeno-type fuzzy inference systems. It applies a combination of the least-squares method and the backpropagation gradient descent method for training the Fuzzy Inference System (FIS) membership function parameters to emulate a given training data set. Also it uses a checking data set for checking the model over fitting. In order to compare the results of ANFIS model, we create an AR model and an ARMA model both of first order.

4 Results

The input variable consists of the time series data for each month. For training the ANFIS we had one input variable with two-membership functions. The output variable consists of the monthly data of next year in every step.

The January monthly data concerns the period from 1974 until 2000. The first 85% of data was used for training and the 15% for checking. The data concerns the electric load of Crete island.

The comparison between the final and the initial membership functions of the input indicates slight differences. The model resulted in sufficient similarity between the initial and the final functions. The membership functions also respected the real shape which is a positive aspect. Their comparison is illustrated in figure 1.

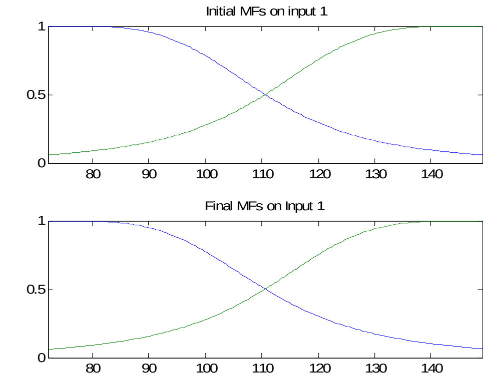

Fig. 1 Comparison initial – final membership function

The graphical representation of the comparison between the actual values and the ANFIS predicted values is presented in the following figure.

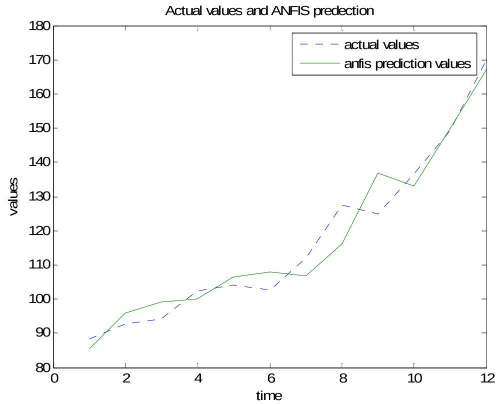

Fig. 2 Comparison actual values - ANFIS prediction

The training error and the step-size evolution are illustrated in figure 3.

Figur

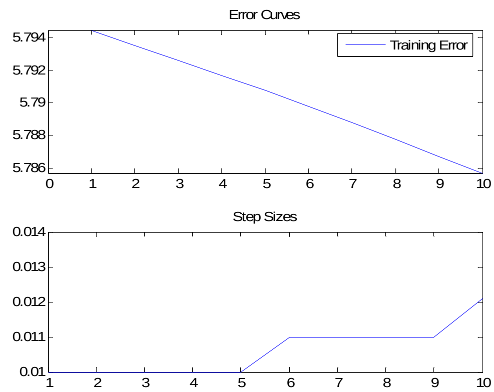

Fig.3 The training error and step-size evolution

The initial step size is defined to 0.01. The step size decrease rate is 0.9 and the step size increase rate is 1.1. The training error goal is set to 0.

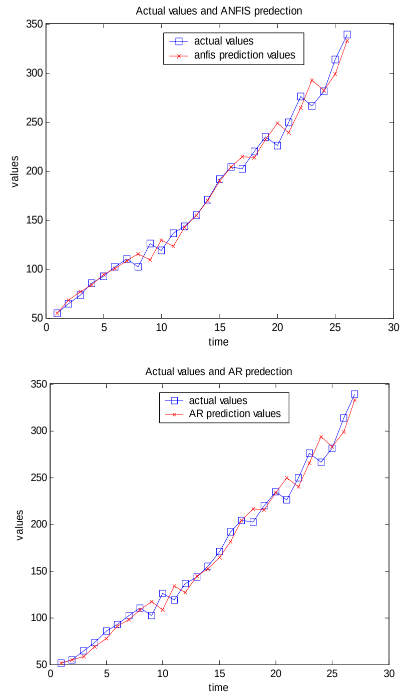

Fig 4. ANFIS and AR Load forecasting diagram

The model was tested many times using different number of epochs. Finally the best results obtained at 20.000 epochs. Figure 4 presents the actual values and the ANFIS and AR prediction values for the January.

A comparison of the main classic error measurements is presented in the next table. The ANFIS model gives higher accuracy compared with the classic forecasting models of AR and ARMA.

	MSE	RMSE	MAE	MAPE
AR	113.51	10.65	7.98	5.07
ARMA	104.13	10.20	7.37	4.75
ANFIS	**102.56**	**10.13**	**7.05**	**4.17**

Table 1. Load forecasting results

5 Conclusion

This paper presents an ANFIS forecasting model that depends on previous load values. For comparison purposes an AR and an ARMA model were developed. The results were presented and compared based on four different kinds of errors. The ANFIS model gives better results than the AR and the ARMA model.

References:

1. Abraham A., Nath B. – A Neuro-fuzzy Approach for Modeling Electricity Demand in Victoria, Applied Soft Computing 1, pp. 127-138, 2001
2. Al-Hamadi H.M., Soliman S.A. – Short-term Electric Load Forecasting Based on Kalman

Filtering Algorithm with Moving Window Weather and Load Model, Electric Power Systems Reseaech xxx, pp. 1-13, 2003

3. Bouqata B., Bensaid A., Palliam R., Skarmeta A. – Times Series Prediction Using Crisp and Fuzzy Neural Networks: A Comparative Study, EEE/IAFE/INFORMS 2000 Conference on Computational Intelligence for Financial Engineering, 2000, USA
4. Chang P. T. – Fuzzy seasonality forecasting, Fuzzy Sets and Systems 90, pg. 1-10, Elsevier Science B. V. 1997
5. Chen T., Wang Mao-Jiung J. – Forecasting methods using fuzzy concepts, Fuzzy Sets and Systems 105, pg. 339-352, Elsevier Science B.V., 1999
6. Dash P.K., Satpathy H.P., Liew A.C. – A Real-time Short-term Peak and Average Load Forecasting System Using a Self-organising Fuzzy Neural Network, Engineering Applications of Artificial Inteligence 11, pp. 307-316, 1998
7. Djukanovic M., Ruzic S., Sobajic D.J., Pao Y-H. – A Neural-net Based Short Term Load Forecasting Using Moving Window Procedure, Electric Power & Energy Systems vol. 17, nr.6, pp. 391-397, 1995
8. Fay D., Ringwood J., Condon M., Kelly M. – Establishing a Solution Strategy for Electrical Demand Forecasting in Ireland,
9. Hagan M., Demuth H., Beale M. – Neural Network Design, Boston MA.: PWS Publishing, 1996
10. Hagan M., Demuth H. – Neural Networks for Controll, American Control Conference, pg. 1642-1656, 1999
11. Hagan M., Demuth H., De Jessus O. – An introduction to the use of Neural Networks in Control Systems, International Journal of Robust and Nonlinear Control, pg. 959-985, 2002
12. Ho S. L., Xie M., Goh T. N. – A comparative study of neural network and Box Jenkins ARIMA modeling in time series prediction, Computers & Industrial Engineering 42, pg. 371-375, , Elsevier Science S.A.
13. Huarng K. – Effective lengths of intervals to improve forecasting in fuzzy time series, Fuzzy Sets and Systems 123, pg. 387-394, 2001, Elsevier Science B.V.
14. Jang, J. S. et al. (1997), Neuro-Fuzzy and Soft Computing-a computational approach to learning and machine intelligence, Prentice Hall, SUA
15. Kalaitzakis K., Stavrakakis G., Anagnostakis E. – Short-term Load Forecasting based on Artificial Neural Networks Parallel Implementation, Electric Power Systems Research 63, pp. 185-196, 2002
16. Kermanshahi B., Iwamiya H. – Up to Year 2020 Load Forecasting Using Neural Nets, Electric Power & Energy Systems 24, pp. 789-797, 2002
17. Kodogiannis V.S., Anagnostakis E.M. – Soft Computing Based Techniques for Short-term Load Forecasting, Fuzzy Sets and Systems 128, pp. 413-426, 2002
18. Nishina T., Hagiwara M. – Fuzzy Inference Neural Network, Neurocomputing 14, Elsevier Science B. V., 1997, pg. 223-239
19. Souza F., Vellasco M., Pacheco M. – The Hierarchical Neuro-fuzzy BSP Model: An Aplication in Electric Load Forecasting, J.Mira and A. Prieto (Eds.): IWANN 2001, LNCS 2084, pp. 174-183, 2001
20. Tamimi M., Egbert R. – Short-term Electric Load Forecasting via Fuzzy Neural Collaboration, Electric Power Systems Reseaech 56, pp. 243-248, 2000
21. Topalli A., Erkmen I. – A Hybrid Learning for Neural Networks Applied to short term load forecasting, Neurocomputing 51, pp. 495-500, 2003
22. Ucenic C., Atsalakis G. – Trade Integration of Goods and Some Technical Sources of Growth, Management of Technological Changes - Proceedings of 3th International Conference on the Management of Technological Changes, Greece, 2003
23. Ucenic C., Atsalakis G. – Study the Influences of the Economic Environment on the Gross Domestic Product Using a Fuzzy Model, Management of Technological Changes-Proceedings of 3th International Conference on the Management of Technological Changes, Greece, 2003
24. *** - MATLAB