LONG – TERM INDUSTRIAL LOAD FORECASTING AND PLANNING USING NEURAL NETWORKS TECHNIQUE AND FUZZY INFERENCE METHOD

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ABSTRACT

Load forecasting plays a dominant part in the economic optimization and secure operation of electric power systems. The plans of the electric power sector have been done and developed with the aid of statistical prediction methods. Electric utility companies need monthly peak and yearly load forecasting for budget planning, maintenance scheduling and fuel management. This paper presents a new approach based on a hybrid fuzzy neural technique which combines artificial neural network and fuzzy logic modeling for long term industrial load forecasting in electrical power systems. An extensive study is carried out to find the accurate forecasting model through an application on an industrial 10 th of Ramadan city in Egypt. Actual record data is used to test the proposed method. A large number of influencing factors have been examined and tested. This paper presents a fully developed system for the prediction of electric maximum demand and consumption for the future 24 months. Also very long-term load forecasting was carried. The strength of this technique lies in its ability to reduce appreciable computational time and its comparable accuracy with other modeling techniques. The outcomes of the study clearly indicate that the proposed composite model of neural network technique and fuzzy inference method can be used as attractive and effective means for the industrial monthly and yearly peak load forecasting. The test results showed very accurate forecasting with the average percentage relative error of 1.98 %.

I INTRODCTION

Industrial peak load forecasting is an essential function in the electric load management field, especially, for the peak demand control of the big companies [1]. Load forecasting plays a dominant part in the economic optimization and secure operation of electric power systems. The high cost and limited resources of primary energy inputs, together with the development of computer and control technologies, provide incentive for the further development of techniques for load prediction for system operation. Electric utilities predict the amount of energy and power that must be delivered to their customers for a variety of time horizons. The techniques of load forecasting may be broadly divided into three areas of applications; these are: Long-term forecasts covering one to ten years ahead monthly and yearly values are used by planning engineers to determine the type and size of the generating plants that minimize both fixed and variable costs. Mid-range forecasts over few months to one year are used by utilities to purchase fuel quantities and to assess revenue impacts due to changes in electricity tariffs. Finally, short-term forecasts, either minute-by-minute or hour-by-hour, are used by electric utility operators to control generating units such as schedule and dispatch. Many classical approaches have been proposed and applied to long-term load forecasting to estimate model parameters, including, least squares errors, least absolute value techniques and kalman filter. Methods based on artificial intelligence such as artificial neural networks, genetic algorithm and expert systems have been proposed and shown promising and encouraging results [2 – 6]. Thus there is a need for accurate load forecasting techniques in general. First, the model that describes the load growth pattern should be selected. Then the parameters of the model should estimated using historical data. The estimated parameters are then used to predict future load values. Finally, the resultant error from the forecasting process should be evaluated. Owing to limitations of computational approaches in terms of computational efforts, historical data requirement and inadequate accuracy of results, emphasis have slowly shifted to the application of artificial neural network (ANN) based approaches to load forecasting. The excellent learning and generalizing capabilities of ANN have made it an automatic choice as a model for forecasting application. The added advantages of these artificial intelligence methods are their capability to learn non-linear mapping and smaller computational efforts [7 –9].

The present article discusses an application of neuro-fuzzy systems to use based forecasting efforts and comparable accuracy make this method more appealing than other techniques for distribution load forecasting. This paper proposes a new hybrid approach of artificial neural network technique and fuzzy inference method for long-term load forecasting. In this paper, an ANN models are employed to forecast the scaled loads. On the other hand, considering the load variation, of the current year and the previous years, a fuzzy inference model forecasts the maximum and the minimum loads. Finally, the annual peak load is predicted by combining the results of the ANN and the fuzzy inference models. The fuzzy rules and the training patterns for the ANN models were collected from the historical load data for the years of 1990 – 2002 of the industrial city 10 th of Ramadan in Egypt.

II FORECASTING PROCEDURE

II.1 Application of ANN in Forecasting Models:

ANNs are finding increasing use as an alternative computational method for solving complex problems like prediction of share prices, weather forecasting, speech and patter recognition, forecasting of electric load etc. Among the various ANN architectures available, the convention: back propagation (BP) momentum learning technique and radial basis function network (RBFN) can be used successfully to forecast distribution load demands. The RBFN was reported to be more accurate and less time consuming [8]. As the input variables pass direct to hidden layers without weights, the RBFN models are simpler compared to BP models. The main problem associated with the use of back propagation in forecasting is its slow convergence, difficulty in generalization and arbitrariness in network design. The RBFN was found to overcome these limitations to a certain extent and was shown to give better results [8]. The global modeling and load modeling are done using RBFNs. The RBFN consists of an input layer and hidden layer of high enough dimensions. The output layer supplies the response of the network to the activation patterns applied to the input layer. In the application of RBFN in global modeling, the observations used to train the model of the load values. The training phase constitutes the optimization of a fitting procedure based on the known data points. In the present work, there is one input layer, one hidden layer and one output layer, as shown in Fig. (1). Three input neurons, two hidden neurons and one output neuron are found to be an adequate combination to give reasonably good training results. The yearly load data collected for the three classes used to train the neural network for each class. To start with, the load data for first, second and third years form the input set and load data for the fourth year is taken as the output for training purposes. Similarly the second training data set is obtained from the second, third and fourth year (input) and the data for the fifth year (output). The model validation is done by finding the forecast error and the confidence interval for the network forecast and is to be within limits.

II.2 Application of Fuzzy Logic Models:

Fuzzy control systems are rule-based systems in which a set of so-called fuzzy rules represents a control decision mechanism to adjust the effects of certain stimulus. The aim of fuzzy control systems is normally to replace a skilled human operator with a fuzzy rule-based system. The fuzzy logic model provides an algorithm, which can convert the linguistic strategy based on expert knowledge into an automatic strategy. Fig. (2) represents the basic configuration of a fuzzy logic system, which consists of a fuzzification, knowledge base, fuzzy interface and a defuzzification [10]. The fuzzy logic method is applied for scoring. The application of fuzzy rules will improve the model accuracy by avoiding arbitrariness for the purpose of the stud. The fuzzy rule base is composed of some rules generated from the analysis of the historical load data. Fuzzy logic Tool box available in MATLAB Soft Package was used [11]. The IF-THEN fuzzy rules used in the presented method.

The structure of ANN and Fuzzy based use forecast is as given in Fig. (3).

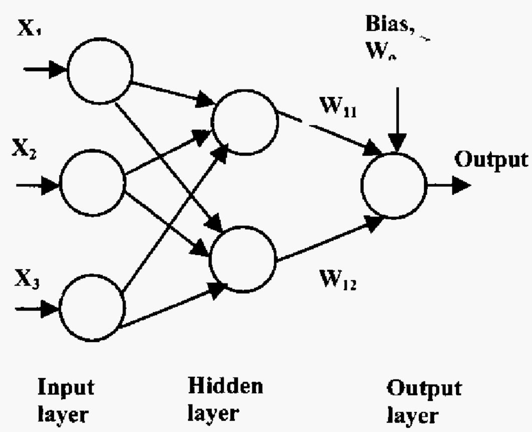

Fig. (1) Radial Basis Function Network structure

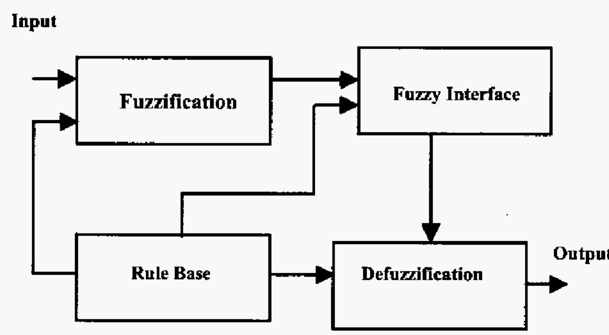

Fig. (2) Block diagram of the fuzzy logic system

III PRACTICAL APPLICATIONS

The proposed method is carried out to find the accurate forecasting model of the peak load demand through an application on industrial Egyptian 10 th of Ramadan city. The actual power load data taken from the Egyptian Electricity Authority of Canal Zone, Sharkia Network. Actual record data is used to perform the study. The data given represents the peak load demand during the period from 1990 to 2002. The data set is divided into two parts. The first ten years, up to 1999, are used to establish an over determine the system. This system is solved using the proposed method to find an estimate for different models parameters. The next part of the data set, from 2000 to 2002, is used to evaluate the estimation process. This is simply by using the parameters obtained from the estimation process to forecast the peak load during the period 2000 – 2002 and compare those values with actual data.

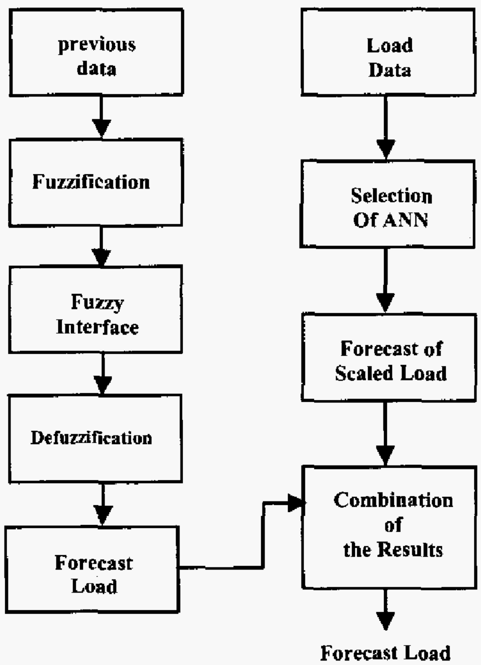

Fig. (3) Structure of ANN and Fuzzy based used in forecasting

IV RESULTS

The fuzzy rules and the training patterns for the ANN models were collected from the historical load data. Every ANN was trained using an error Back Propagation algorithm (BP) and Radial Basis Function Network (RBFN) with an adaptive learning rate and momentum [9]. The number of training cycles has been determined through a trial process, to avoid over-training. In this study, the actual data and the incremental data which to take into account the differences between the present and previous data has been used. The major simulation has been carried out. In addition, the designed BP and RBFN networks have been compared to verify their effectiveness for out proposed long - term and very long - term load forecasting. The obtained results are as follows:

1. RBFN and BP were trained with 10 years of incremental and actual data (1990 –1999), and then the conducted forecast for next monthly peak load for 24 months. Fig. (4) shows the forecasting monthly peak load for (24 months) two years (2001-2002). Fig. (5) shows the percentage errors of forecasted monthly peak loads for the same two years.

2. In the next stage, the candidate network was trained with 10 years of data (1990 –1999) to forecast the yearly peak loads. After training, peak loads of next 3 years (2000 – 2002) were forecasted. Fig. (6) shows forecasting the yearly peak loads of three years (2000 –2002). Fig. (7) shows the percentage errors of forecasted yearly peak loads.

3. Finally, very long-term load forecasting was carried out for years 2004, 2005, 2010, 2015 and 2020 as shown in Fig. (8).

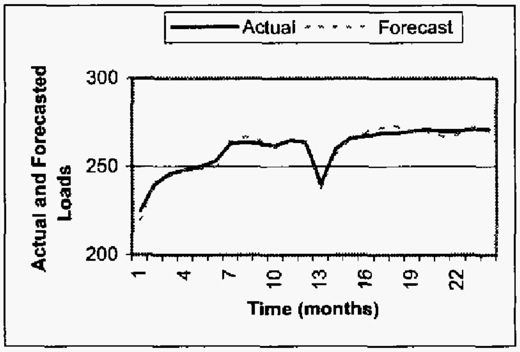

Fig. (4) Actual and Forecasted Monthly Peak Loads (MW) for Two Years (2001 and 2002)

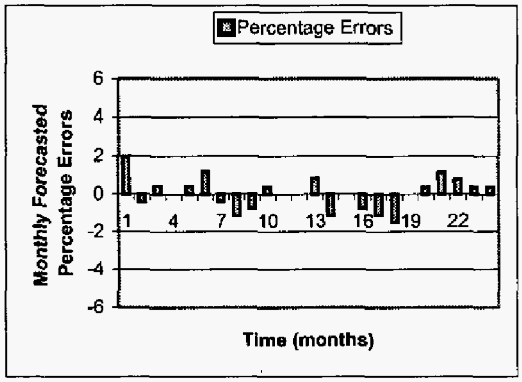

Fig. (5) Percentage Errors of Forecasted Monthly Peak Loads for Two years (2001 and 2002)

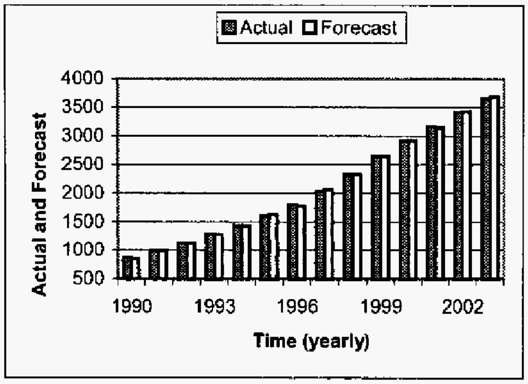

Fig. (6) Actual and Forecasted Yearly Loads (MW) for 14 years (1990 –2003)

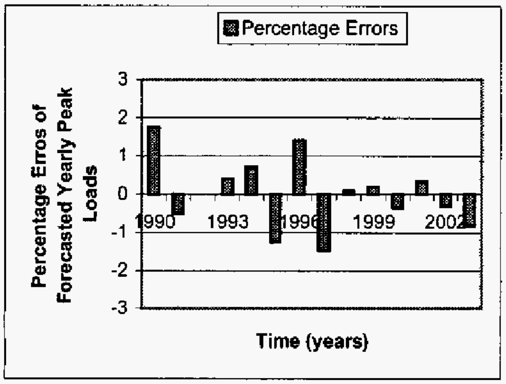

Fig. (7) Percentage Errors of Forecasted Yearly Peak loads for 14 years (1990 – 2003)

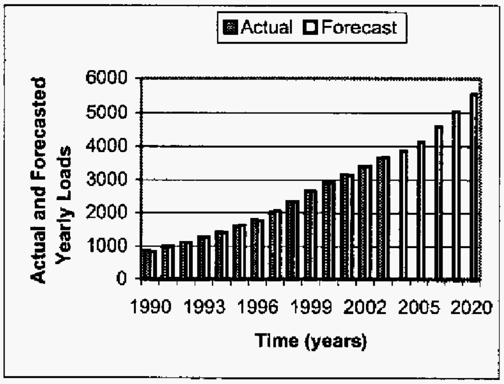

Fig. (8) Forecasting the peak loads (MW) of 2004, 2005, 2010, 2015, and 2020 (Training data: 1990-2003)

It has been demonstrated that the proposed BP and RBFN give relatively accurate load forecasts for the actual data. One of the important points for forecasting the long-term load is to take into account the past and present economic situations and power demand. These points were considered in this study. The proposed methods have also showed that the changes in loads are reflection of economy. Moreover, the proposed model gives much better forecasting results with the overall average percentage error of 1.98 %. Generally, 10 % forecasting error is said to be acceptable for long-term load forecasting of power companies [12]. However, our previous results have shown its ability to forecast the future loads with only 1.98 % error.

V CONCLUSIONS

This paper introduces a new research work conducted to improve the long-term load forecasting, which was a difficult task using conventional methods. The proposed approach using ANN and fuzzy inference method. The benefit of the proposed hybrid structure was to utilize the advantages of both, i.e, the generalization capability of ANN and the ability of fuzzy inference for handling and formalizing the experience and knowledge of the forecasters. It has been demonstrated that the proposed method give relatively accurate load forecasts for the actual data. The forecasting methodology presented in this paper has been applied successfully to forecast the peak load for a fast developing power system in the industrial city 10 th of Ramadan , Egypt. The test results showed that the proposed forecasting method could provide a considerable improvement of the forecasting accuracy. This indicates that the fuzzy rules and the training patterns for the ANN is quite promising and deserve serious attention of its robustness and suitability for implementation. It can be concluded that the outcome of the study clearly indicates that the proposed composite model can be used as an attractive and effective means for the industrial load forecasting. The improvement of forecast accuracy and the adaptation to the change of customers would fulfill the forecasting needs.

VI REFERENCES

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