# Power Systems Load Predictions Assessment for the Kingdom of Bahrain

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***Abstract:***

*The Kingdom of Bahrain electrical system requires an effective quantitative assessment of load prediction of the power system network.The basic information, the suitable mathematical models and the realistic rates are needed for this type of assessment. The paper will highlights on the important information generated to help the study, such as the loads during a number of years (1996-2001). Also, some of these information is the maximum, minimum, and the average loads. The maximum peaks occur are carried out. By means of load duration curve, the probabilities of having various amounts of capacity unavailable are combined with the system load. Electrical power generation energy reliability evaluation regarding planned maintenance algorithm was developed and implemented.*

*The demand of electric energy in Kingdom of Bahrain has grown rapidly. This required a load management that can contribute to the lowering of peak load. In the present research a new model is presented and proposed. The model is different from other similar models. The behaviour of the load over a period of time can be summarized using a histogram.*

*In recent years, a large amount of literature has evolved on the use of artificial neural networks (ANN) for electrical load forecasting. Accurate load forecasts load forecasts are required by utilities who need to predict their costomers' demand. A load forecast is produced by substituting a forecast for each weather variable in the artificial neural networks (ANN) model. A wide variety of methods have been used for load forecasting. When forecasting from nonlinear models, such as artificial neural networks (ANN), it is important to be aware that the expected value of a nonlinear function of random variables is not necessarily the same as the nonlinear function of the expected values of the random variables. The expected results will show that using weather ensemble predictions, instead of the traditional approach of using single weather point forecast, led to improvements in accuracy for all lead times.*

***Key words:***
*Genetic Algorithm, Neuro-Fuzzy, Electric Load, and Load Forecasting.*

**Introduction:**

Neural networks and fuzzy systems have been extensively applied to many problems including system identification, time series prediction, classification and control. The distribution of electrical load forecasting methods are generally classified into time series. The limitations of conventional approached 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 ANN based forecasting models, regardless of their level of sophistication, can handle only numerical data [1,2]. The Fuzzy Logic based approach can replaced the heuristic method which is used in

the conventional modeling of use based method of distribution load forecasting. Fuzzy transparency allows the incorporation of domain expert knowledge and humanistic verification and validation of the identified models. Unitil recently neurofuzzy algorithms have been restricted to low dimensional problems where either the expert knowledge or empirical data is of a sufficiently high quality. There are a number of applications of neurofuzzy technology. Some of these applications are model building, fusion of numeric data and linguistic information, business rule extraction and explanation process, and incorporation of personal preference.
Lee and Lee [3] are the first who worked on neurofuzzy systems, especially on fuzzy neural networks. Unfortunately, they did not give any training laws for the network.

Sharma and Kothari in their paper present a new approach for real time tuning of a dual input power system stabilizer using neuro-fuzzy system (NFS) [4]. The NFS is fuzzy inference system implemented in the framework of multi-layered feed forward adaptive network. NFS is trained using hybrid training algorithm for real-time tuning of the dual input power system stabilizer. Padmakumari et al [5] in their article describe the application and validation of forecasting results of a hybrid fuzzy neural technique which combines neural network and fuzzy logic modeling for long term land use based distribution load forecasting. The use of fuzzy logic effectively handles the load distribution in a small area with future demand of consumer class.The use of fuzzy neural network was extensively tested on actual data obtained from a small power distribution system.

**Results and Discussion:**
In this paper, an application of neurofuzzy technique is presented for the estimation of maximum average and minimum system load for the given year and month. The neurofuzzy algorithm is used to establish an approximate relation between inputs “Year and month” and outputs “maximum average and minimum system load”. The origin of neurofuzzy inference systems is to incorporate neural concepts, such as learning and parallelism, into fuzzy logic inference systems (fuzzy system, in the context of system applications).

The Neuro-Fuzzy system has some rules. One of which is that the fuzzy reasoning rules can be divided into four main types. For simplicity, only the two-input single-output model of the neurofuzzy system is now presented in this paper. Four types of the fuzzy rules can written as follows:

IF $x_1$ is $A_1$ AND $x_2$ is $A_2$ THEN $y$ is $B$, (1)

IF $x_1$ is $A_1$ AND $x_2$ is $A_2$ THEN $y$ is $z$, (2)

IF $x_1$ is $A_1$ AND $x_2$ is $A_2$ THEN $y$ is $f(x_1, x_2)$, (3)

IF $x_1$ is $a_{j,1}$ AND $x_2$ is $a_{j,2}$ THEN $y$ is $z$, (4)

where $x_i$ is the $i_{th}$ input variable, and $A_i$ is the one of the linguistic variables defined for it.

The fuzzy output variable $y$ is defined separately for each rule. In the first rule, the consequence of the rule is fuzzy set $B$, while the second rule uses a singleton. The consequence of third rule is a function of the input variable [6]. The antecedent part of the fourth rule uses the reference values $a_{j,i}$, when the firing strength of the rule is computed by measuring the distance between the inputs and the references [7]. The results obtained are given in Figures 1 (maximum loads), 2 (minimum loads), and 3 (average loads). The figures show the varies of the load and the predicted loads for Kingdom of Bahrain through the years 1996 up to 2001. The studied network was carried-out for the load prediction of the maximum, minimum, and average for the loads values through the years mentioned earlier. The actual values on the simulator of the Kingdom of Bahrainnetwork have been taken the consideration to verify the proposed algorithm. The three curves (Figures 1-3) show the training carried-out of the Genetic Algorithm of the rule base on the performance of the network as illustrated. The first figure shows the actual loads and the trained values of the maximum values. An error with a percentage of approximately 3.5 noticed of the year 1997. This error happened based on a fault occurred on the network (generation side). The rest of the results (the actual and the trained values has a less percentage error or almost the same). The errors are less than three and a half percent or identical are applicable for the minimum and average values of the loads through the considered years.

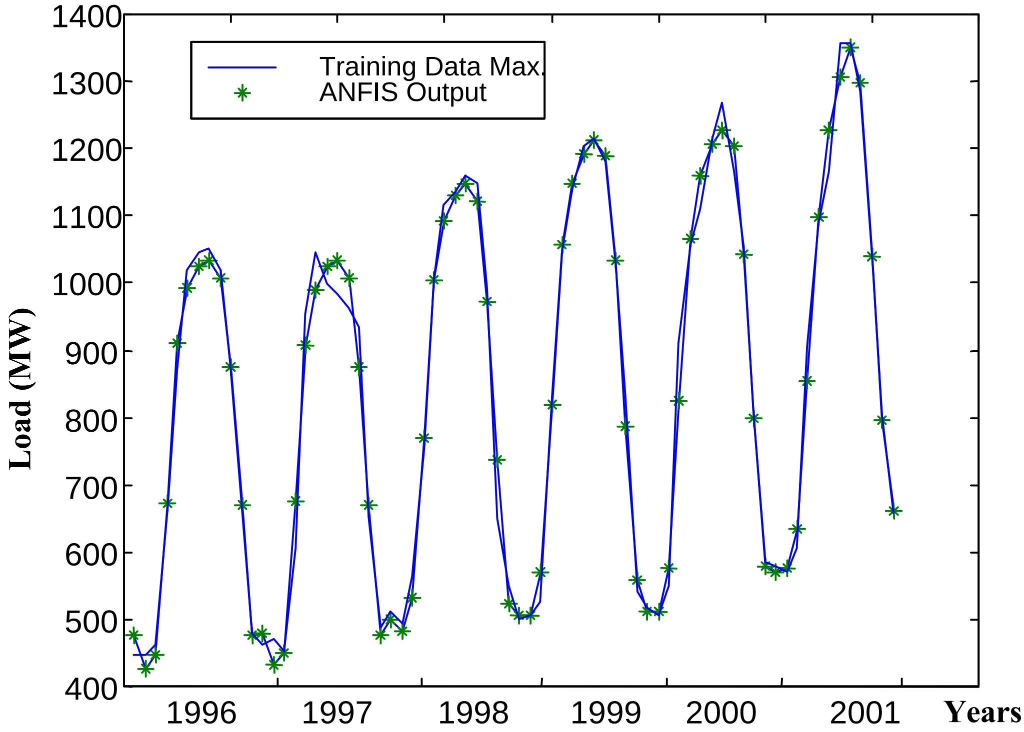


Fig. (1) the maximum actual and the trained loads through the years 1996-2001
(Load vary between 400MW and 1400MW)

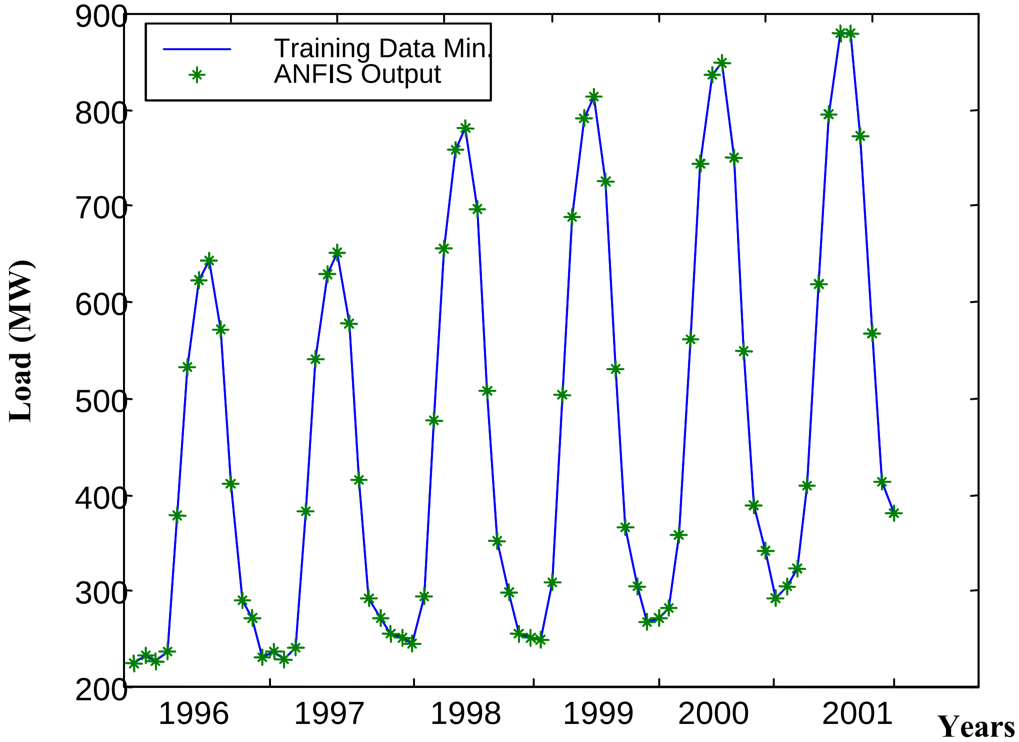


Fig. (2) the minimum actual and the trained loads through the years 1996-2001
(Load vary between 200MW and 900MW)

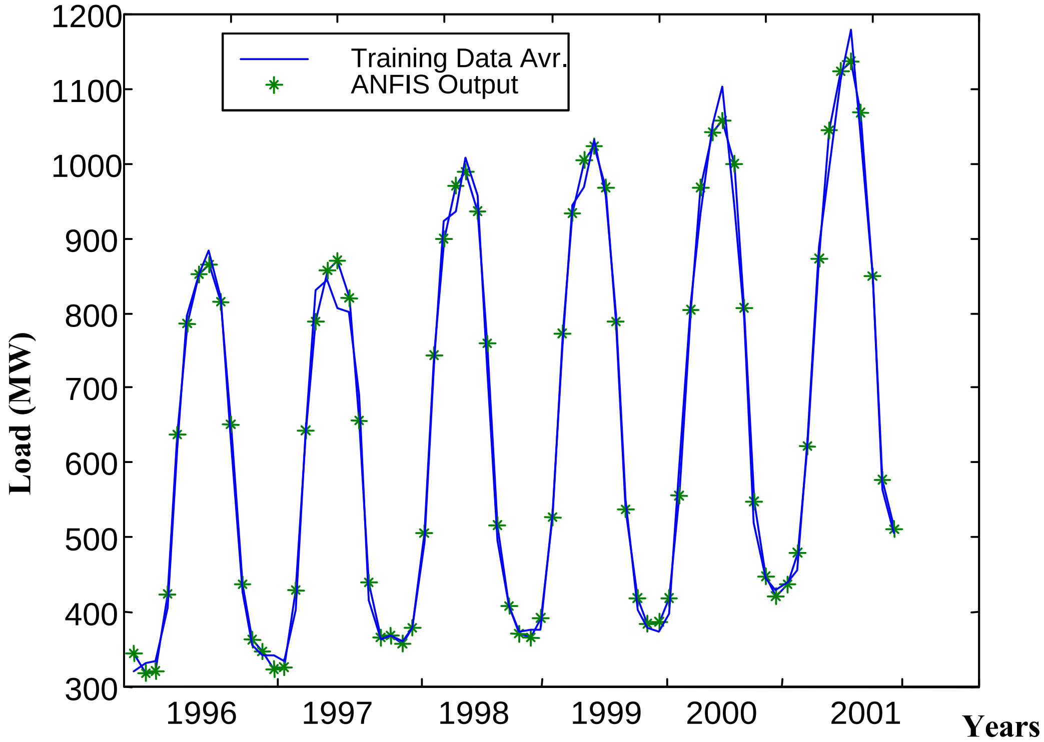


Fig. (3) the minimum actual and the trained loads through the years 1996-2001
(Load vary between 300MW and 1200MW)

**Conclusion:**

An important consideration when modelling system behaviour to understand the issues revolving around the expected and predicted loads. The present study highlighted the difference between the actual load and the predicted load (by training through the Fuzzy Logic Training). This is the particular interest to the modelling system through the years 1996 to 2001 by considering the maximum, minimum, and average loads of the Kingdom of Bahrain. However, through the present study, the analysis demonstrates a very low error in the month of July 1997. In the maximum load only results, but almost the same –by training- as in the actual loads. The reason of this small error based on a load shedding occurred on the netwok at that instant. The present approach helped in identifying the load prediction through training –by genetic algorithm- which is critical to selecting an appropriate and suitable model to completing system analysis. It van be considered that the presented model is very accurate.

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