

Application of Neural Networks In Short-Term Load Forecasting

Dr.MOHSEN HAYATI– BEHNAM KARAMI

Electrical Engineering Department
Faculty of Engineering
Razi University
Kermanshah
IRAN

Abstract: Artificial neural network is a computational intelligence technique that has found major applications in engineering and science. One of them is to design short-term load forecasting systems (STLF) which due to its complicated and nonlinear nature, the study of these systems requires an efficient computational tool which neural networks can do it well. In this paper we explore the use of neural networks to study the design of STLF Systems. We use the three important architectures of neural networks named Multi Layer Perceptron (MLP), Elman Recurrent Neural Network (ERNN) and Radial Basis Function Network (RBFN) to model STLF systems. The results show that RBFN networks have the minimum forecasting error and are the best method to model the STLF systems.

Key Words: Load Forecasting – MLP – ERNN – RBFN

1 INTRODUCTION

Prediction of future values of temporal series is a common problem and is largely and amply divulged on scientific literature. Economists aim to predict economic tendencies, meteorologists the weather conditions, stockholders would like to predict future prices of stock market. Interest field on forecasting is so vast that justifies the huge quantity of prediction methods, since long ago, well established.

However, Artificial Neural Network (ANN) has been replacing traditional methods in many applications offering, besides a better performance, a number of advantages: no need for system model, bizarre tolerance patterns, notable adaptive capability and so on. Load forecasting is one of the most successful applications of ANN in power systems.

Short term load forecasting (STLF) refers to forecasts of electricity demand (or load), on an hourly basis, from one to several days ahead. The short term load forecasting (one to twenty four days) is of importance in the daily operations of a power utility. It is required for unit commitment, energy transfer

scheduling and load dispatch. With the emergence of load management strategies, the short term load forecasting has played a greater role in utility operations. The development of an accurate, fast and robust short-term load forecasting methodology is of importance to both the electric utility and its customers.

Many algorithms have been proposed in the last few decades for performing accurate load forecasting. The most commonly used techniques include statistically based techniques like time series, regression techniques and box-jenkins models, expert system approaches and ANNs.

For developing the forecasting models, we used the actual hourly electrical load data provided by the Kermanshah electric power utility for the years 1999 through 2003. The weather parameters temperature, humidity and wind speed affect the forecasting accuracy and are included in the model. To ascertain the forecasting accuracy, the developed models were tested on the data for the year 2004.

2 LOAD DEMAND PATTERN

A broad spectrum of factors affects the system's load level such as trend effects, cyclic-time effects, weather effects, random effects like human activities, load management and thunderstorms. Thus the load profile is dynamic in nature with temporal, seasonal and annual variations. In this paper we develop a system with 30 input parameters (past 24 hours load, weather conditions and day of the week) to forecast 24 ahead load demands (output) using artificial neural networks (Fig.1).

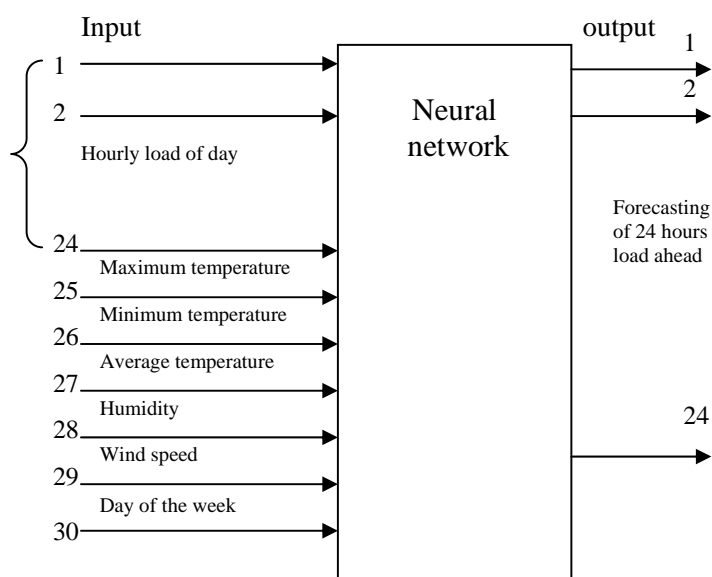


Fig.1. Input-output schematic of system.

3 COMPUTATIONAL INTELLIGENCE MODELS

In this paper we use three models of neural networks which are selected among the main network architectures used in engineering.

The basis of all models is neuron structure. These neurons act like parallel processing units. (Fig.2)

3.1 Multilayer perceptron

We used a fully connected feed forward type neural network consisting of one hidden layer (Fig.3). Back propagation algorithm was utilized for training. The optimal number of hidden neurons was obtained experimentally by changing the network design and running the training process several times until a good performance was obtained.

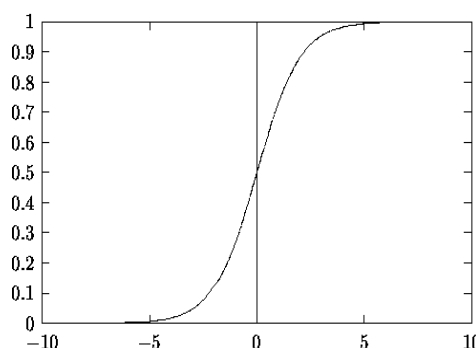
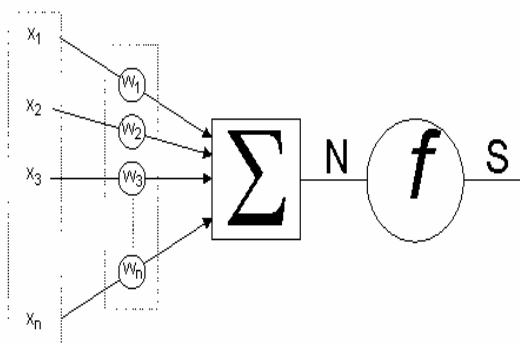


Fig.2. Neuron model and excitation function.

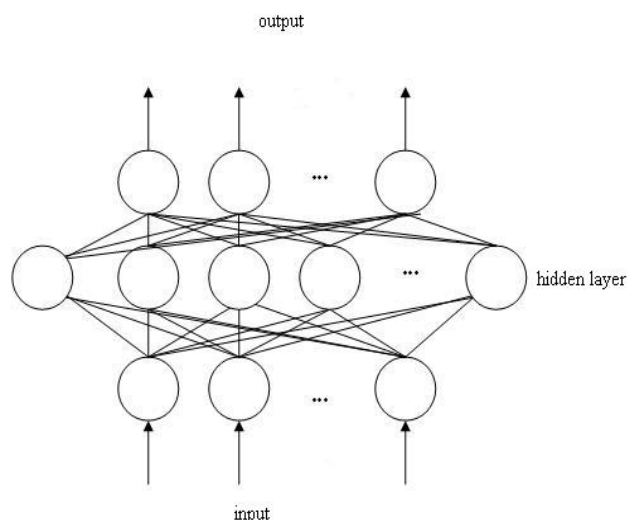


Fig.3. Multilayer perceptron network.

Comparison of 24 hours ahead load forecasting using MLP and exact load is given in Fig.4.

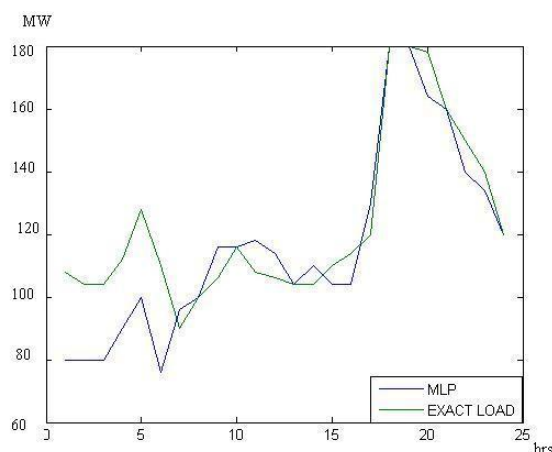


Fig.4.Comparison of 24 ahead loads forecasting with MLP network and exact loads.

3.2 Elman recurrent neural network

Recurrent neural networks, being member of a class of neural network models and exhibiting dynamic behavior, are often used to represent dynamic systems. Due to the nonlinear nature of these models, the behavior of the load prediction system can be captured in a compact, robust and more natural representation. We used the Elman network (Fig.5) with one hidden layer. In this network, the outputs of the hidden layer are allowed to feedback onto itself through a buffer or context layer. This feedback allows Elman networks to learn to recognize and generate temporal patterns, as well as spatial patterns. Every hidden neuron is connected to only one neuron of the context layer through a constant weight of value one. Hence, the context layer constitutes a kind of copy or memory of the state of the hidden layer, one instant before. The number of -Context neurons are consequently the same as the number of hidden neurons. Every neuron in the hidden layer receives the outputs of the context layer neurons as input, in addition to the external inputs of the network. Input, output and context neurons have linear activation functions while hidden neurons have Sigmoidal activation function.

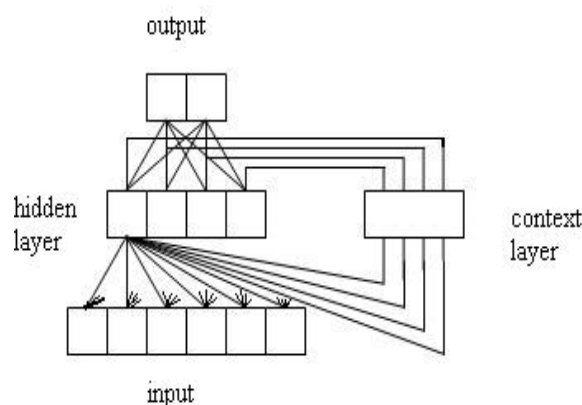


Fig.5.Elman recurrent neural network.

Comparison of 24 hours ahead load forecasting using ERNN and exact load is given in Fig.6.

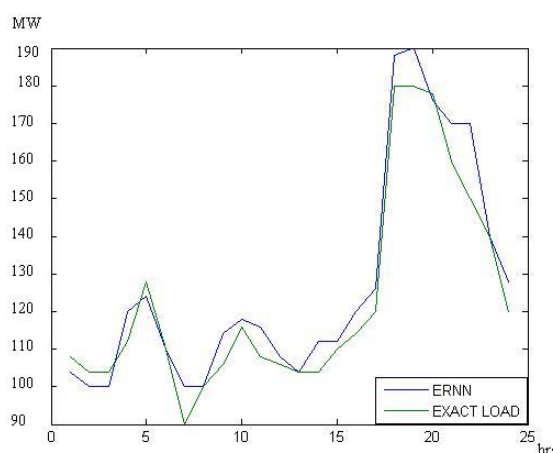


Fig.6.Comparison of 24 hours ahead load forecasting with ERNN network and exact load.

3.3 Radial basis function network

Radial Basis Function Network (RBFNs), exhibit a good approximation and learning ability and are easier to train and generally converge very fast. The RBFN is a 3-layered feed forward network (Fig.7) comprising of input, hidden/memory, and output neurons respectively. It uses a linear transfer function for the output units and Gaussian function (radial basis function) for the hidden units (Fig.8).

The training of network accomplishes in two sections; first in an unsupervised manner the

parameter of Gaussian function of hidden layer is tuned with k-mean clustering algorithm, then the weights between hidden layer and output layer are set with supervised learning algorithm like back propagation algorithm.

The equivalent functional behaviors of RBFN and takagi-sugeno fuzzy model show that the use of RBFN has the same result with designing the system with takagi-sugeno fuzzy methods.

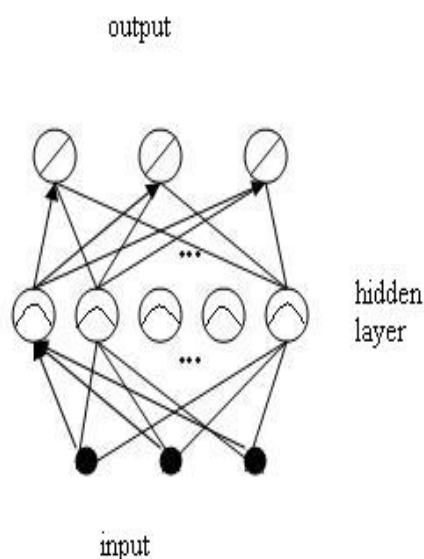


Fig.7.Radial basis function network.

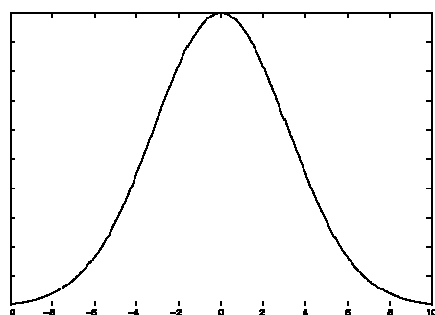


Fig.8.Gaussian excitation function.

Comparison of 24 hours ahead load forecasting using RBFN and exact load is given in Fig.9.

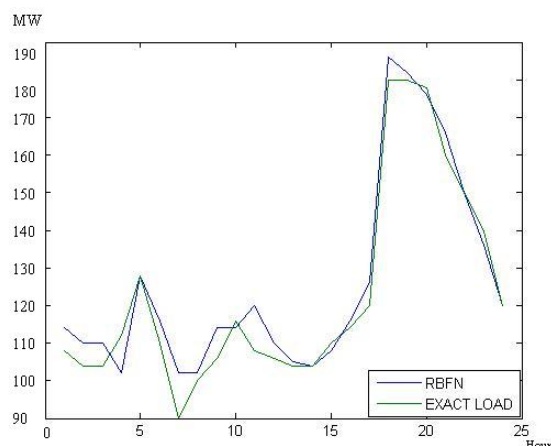


Fig.9.Comparison of 24 hours ahead load forecasting with RBFN network and exact load.

4 TEST RESULT AND DISCUSSION

The assessment of the prediction performance of the different soft computing models was done by quantifying the prediction obtained on an independent data set. The mean absolute percentage error (MAPE) were used to study the performance of the trained forecasting models for the testing year.

MAPE is defined as follows:

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left[\frac{P_{actual,i} - P_{predicted,i}}{P_{actual,i}} \right] \times 100$$

Where $P_{actual,i}$ is the actual load on day i and $P_{predicted,i}$ is the forecast value of the load on that day. Where N represents the total number of hours. The results are shown in table 1.

Comparison of all computational method for 24 hours ahead load forecasting and exact load is shown in Fig.10.

Table.1.Comparison of MAPE index for Three types of neural network.

Neural network	MLP	ERNN	RBFN
MAPE%	9.3	4.1875	3.729

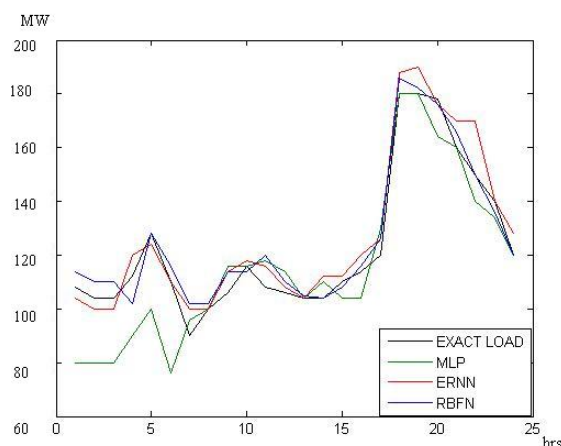


Fig.10.Comparison of all computational method for 24 hours ahead load forecasting and exact load.

5 CONCLUSIONS

A comparative study of soft computing models for load forecasting shows that RBFN is more accurate and effective as compared to MLP and ERNN. The error associated with each method depends on several factors such as the homogeneity in data, the choice of model, the network parameters, and finally the type of solution. ANNs have gained great popularity in time-series prediction because of their simplicity and robustness. The learning method is normally based on the gradient descent method _ back propagation algorithm. Back propagation algorithm has major drawbacks: the learning process is time-consuming and there is no exact rule for setting the number of hidden neurons to avoid over fitting or under fitting, and hopefully, making the learning phase convergent. In order to eliminate such problems, the RBFN has been applied. The results obtained clearly demonstrate that RBFN are much faster and more reliable for short term load forecasting.

Acknowledgement

We would like to express our gratitude to Mr. Gholam Reza Khoshkholgh, the manager of west regional electrical company and his assistant Mr. Ali Talebianfar for providing us the required data.

References:

- [1] K.Y.Lee-J.H.Park, Short Term Load Forecasting Using An Artificial Neural Network, Transactions On Power Systems, Vol.7, No 1, February 1992
- [2] J.N.Fidalgo - J.A.Pecas Lopes, Load Forecasting Dealing With Medium Voltage Network Reconfiguration, ESANN'2000 Proceedings, European Symposium On Artificial Neural Networks, Bruges (Belgium), 26-28 April 2000
- [3] P.K.Dash - H.P.Satpathy - A.C.Liew, A Real-Time Short-Term Load Forecasting System Using Functional Link Network, IEEE Transactions On Power Systems, Vol.12, No.2, May 1997
- [4] T.Matsui - T.Iizaka, Peak Load Forecasting Using Analyzable Structured Neural Network, IEEE PES 2001 Winter Meeting, January 28 - February 1, 2001, Columbus, Ohio USA
- [5] D.Fay - J.V.Ringwood - M.Condon, On The Influence Of Weather Forecast Errors In Short-Term Load Forecasting Models, Control 2004, University Of Bath, UK, September 2004
- [6] L. R. Medsker - L. C. Jain, Recurrent Neural Networks Design And Applications, Washington D.C., CRC Press 2001
- [7] A. K. Jain - Jianchang Mao, Artificial Neural Networks: A Tutorial, IBM Almaden research Center, March 1996
- [8] Koch christof, Neural Network Networks Algorithms - Applications And programming Techniques, California Institute Of Technology, Addison-Wesley Publishing Company 1991