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Artificial Neural Network Approach for Short Term Load Forecasting for Illam Region

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Abstract**—**In this paper, the application of neural networks to study the design of short-term load forecasting (STLF) Systems for Illam state located in west of Iran was explored. One important architecture of neural networks named Multi-Layer Perceptron (MLP) to model STLF systems was used. Our study based on MLP was trained and tested using three years (2004-2006) data. The results show that MLP network has the minimum forecasting error and can be considered as a good method to model the STLF systems.

Keywords**—**Artificial neural networks, Forecasting, Multi-layer perceptron.

I. INTRODUCTION

NUMEROUS advances have been made in developing intelligent systems, some inspired by biological neural networks, fuzzy systems and combination of them. Researchers from many scientific disciplines are designing Artificial Neural Network (ANNs) to solve a variety of problems in pattern recognition, prediction, optimization, associative memory and control. Conventional approaches have been proposed for solving these problems. Although successful applications can be found in certain well-constrained environments, none is flexible enough to perform well outside its domain. Artificial Neural Network has been replacing traditional methods in many applications offering, besides a better performance, a number of advantages: no need for system model, tolerance bizarre patterns, notable adaptive capability and so on. Load forecasting is one of the most successful applications of ANN in power systems. Neuro-Fuzzy (NF) computing is a popular framework for solving complicated(complex) problems. If we have knowledge expressed in linguistic rules, we can build a Fuzzy Interface System (FIS), and if we have data, or can learn from a simulation (training) then we can use ANNs. For building an FIS, we have to specify the fuzzy sets, fuzzy operators and the knowledge base.

Similarly, for constructing an ANN for an application the user needs to specify the architecture and learning algorithm. An analysis reveals that the drawbacks pertaining to these approaches seem to be complementary and therefore it is natural to consider building an integrated system combining the concepts. While the learning capability is an advantage from the viewpoint of FIS, the formation of linguistic rule base will be the advantage from the viewpoint of ANN.

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 hours) 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-jenkis models[1] and computational intelligence method like fuzzy systems, ANNs[2,3,4,5,6,7] and neuro-fuzzy systems.

For developing the forecasting models, we used the actual hourly electrical load data provided by the west electric company for the years 2004 through 2006 for the Illam state located in the west of Iran .The weather parameters temperature, humidity, wind speed, season(month) and day of the week 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 years 2004-2006.

II. 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 as shown in Fig. 1 with inputs parameters such as past 24 hours load, temperature, humidity ,wind speed, season(month) and day of the week to forecast 24 hours ahead load demands(output) for the Illam state located in the west of Iran using artificial neural networks.

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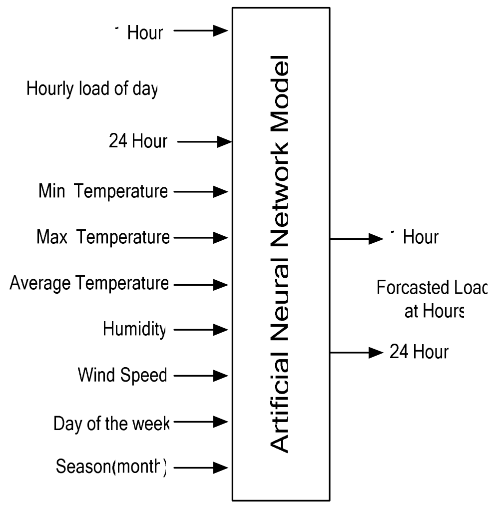


Fig. 1 Input-output schematic of system

III. THE NEURAL NETWORK MODEL

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. Neural networks resemble the human brain in the following two ways:

i- A neural network acquires knowledge through learning.
ii- A neural network's knowledge is stored within inter-neuron connection strengths known as synaptic weights.

The true power and advantage of neural networks lies in their ability to represent both linear and non-linear relationships and in their ability to learn these relationships directly from the data being modeled. Traditional linear models are simply inadequate when it comes to modeling data that contains non-linear characteristics. In this paper, one model of neural network is selected among the main network architectures used in engineering. The basis of the model is neuron structure as shown in Fig. 2. These neurons act like parallel processing units. An artificial neuron is a unit that performs a simple mathematical operation on its inputs and imitates the functions of biological neurons and their unique process of learning. From Fig. 2 will have**,**

$$v_k = \sum_{j=1}^{m} x_j w_{kj} + b_k$$

The neroun output will be

$$y_k = f\left(v_k\right)$$

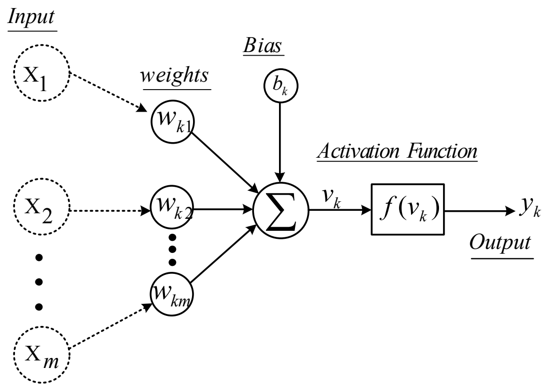


Fig. 2 Neuron model

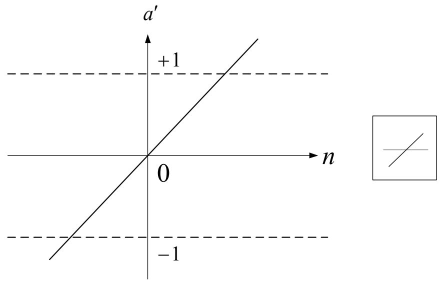
Some of the transfer functions are shown in Fig. 3.

A. Multi-Layer Perceptron

ANNs are characterized in principle by a network topology, a connection pattern, neural activation properties, train strategy and ability to process data. The most common neural network model is the multilayer perceptron [8,9]. This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown.

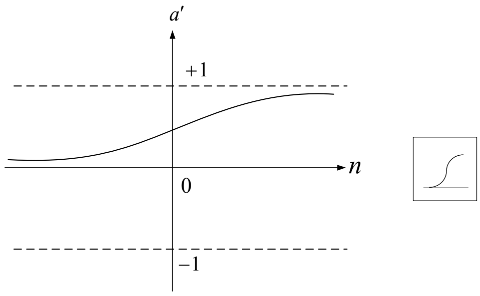
Fig. 4 shows the block diagram of a two hidden layer multiplayer perceptron (MLP). The inputs are fed into the input layer and get multiplied by interconnection weights as they are passed from the input layer to the first hidden layer. Within the first hidden layer, they get summed then processed by a nonlinear function (usually the hyperbolic tangent). As the processed data leaves the first hidden layer, again it gets multiplied by interconnection weights, then summed and processed by the second hidden layer. Finally the data is multiplied by interconnection weights then processed one last time within the output layer to produce the neural network output. To perform any task, a set of experiments of an input-output mapping is needed to train the neural network. These data are one of the most important factors to obtain reliable results from any trained ANN. Thus, the training sample data have to be fairly large to contain all the required information and must include a wide variety of data from different experimental conditions and process parameters.

Back propagation training algorithms are often too slow for practical problems, so we can use several high performance algorithms that can converge from ten to one hundred times faster than back propagation algorithms. These faster algorithms fall into two main categories: heuristic technique (variable learning rate back propagation, resilient back propagation) and numerical optimization techniques (conjugate gradient, quasi-Newton, Levenberg-Marquardt). We tried several of these algorithms to get the best result. Levenberg-Marquardt is the fastest algorithm but as the number of weights and biases in the network increase, the advantage of this algorithm decrease, so we tried another algorithm which perform well on function approximation and converge rather fast. From these algorithms, conjugate gradient was suitable for our purpose.



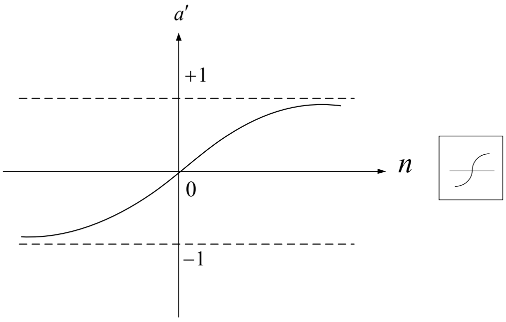
$a' = purelin(n)$

Linear Transfer Function



$a' = \log sig(n)$

Log – sigmoid Transfer Function



$a' = \tan sig(n)$

Tan-Sigmoid Transfer Function

Fig. 3 Three type of transfer function

Neural networks generally provide improved performance with the normalized data. The use of original data as input to neural network may cause a convergence problem. All the data sets were therefore, transformed into values between -1 and 1 through dividing the difference of actual and minimum values by the difference of maximum and minimum values subtracted by 1. At the end of each algorithm, outputs were denormalized into the original data format for achieving the desired result. We know that from one initial condition the algorithm converged to global minimum point, while from another initial condition the algorithm converged to a local minimum so it is better to try several different initial conditions in order to ensure that optimum solution has been obtained [10,11].

Training goal for the networks was set to 10^{-5}. Finding appropriate architecture needs trial and error method. Networks were trained for a fixed number of epochs. By this way, we found that 17 neurons for hidden layer at 1000 epochs produce good result. Comparison of 24 hours ahead load forecasting with MLP and exact load is shown in Fig. 5.

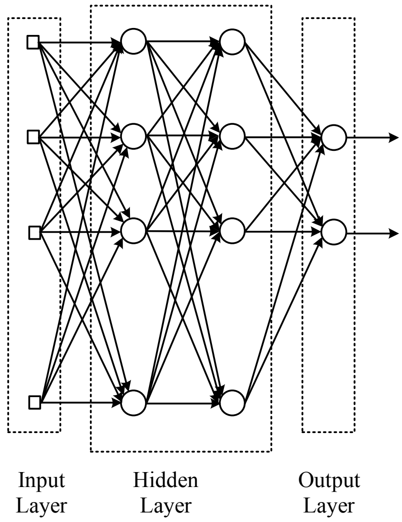


Fig. 4 Neural network architecture for short term load forecasting

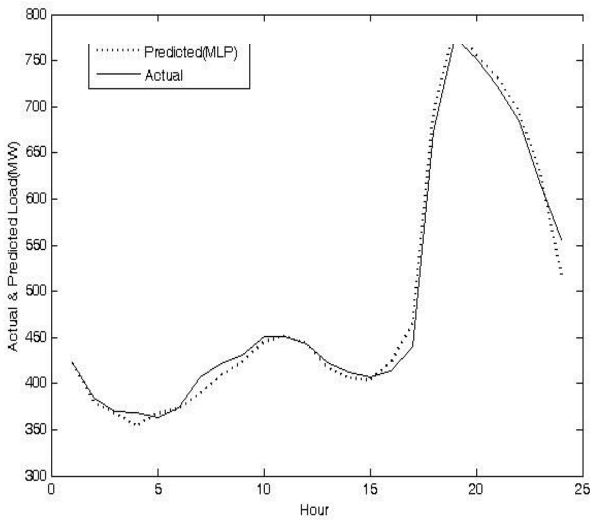


Fig. 5 (a) Comparison of 24 hours ahead load forecasting using MLP and exact load for 8-May-2004

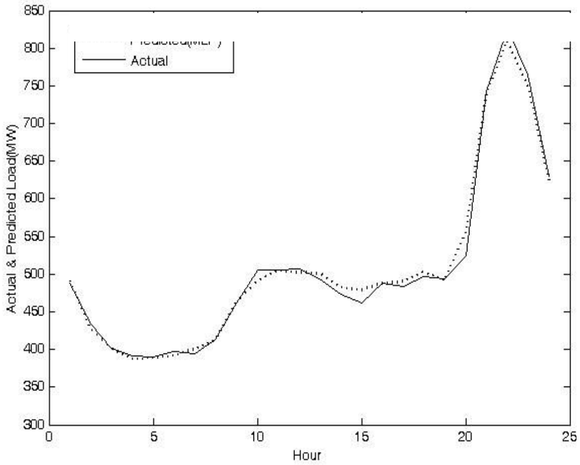


Fig. 5 (b) Comparison of 24 hours ahead load forecasting using MLP and exact load for 19-Nov-2005

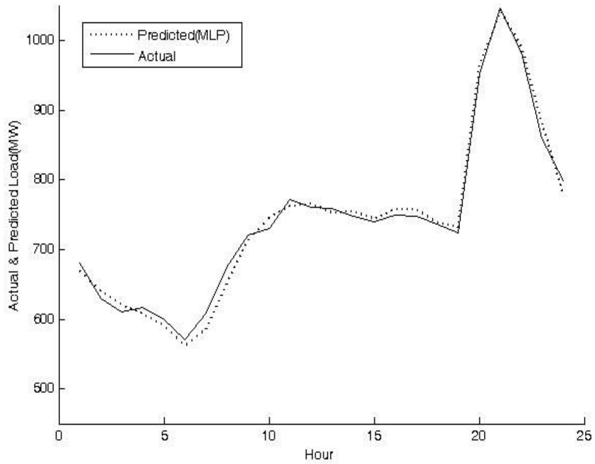


Fig. 5 (c) Comparison of 24 hours ahead load forecasting using MLP and exact load for 25-July-2006

IV. 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) was used to study the performance of the trained forecasting models for the testing years. MAPE *is* defined as follows:

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

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 data (hours). The mean absolute percentage error (MAPE) results are shown in Fig. 6. The optimal structures for developed MLP neural network for obtaining minimum forecasting error is shown in Table I. It has been observed that error depends on several factors such as the homogeneity in data, the choice of model, the network parameters, and finally the type of solution. From the result shown in Fig. 5 and Table I, it is observed that the predicted values are in good agreement with exact values and the predicted error is very less. Also the results obtained clearly demonstrate that MLP method is reliable and accurate and effective for short term load forecasting. Therefore the proposed ANN model with the developed structure shown in Table I can perform good prediction with least error.

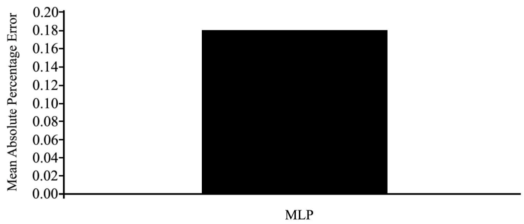


Fig. 6 Mean absolute percentage error

TABLE I
MLP Structure

Neural Network	MLP
Number of hidden layer	1
Number of hidden neuron	17
Activation function used in hidden layer	tan-sigmoid
Activation function used in output layer	pure linear
MAPE	0.18

V. Conclusion

The result of MLP network model used for one day ahead short term load forecast for Illam State located in west of Iran, shows that MLP network has a good performance and reasonable prediction accuracy was achieved for this model. It's forecasting reliabilities were evaluated by computing the mean absolute error between the exact and predicted values. The results suggest that ANN model with the developed structure can perform good prediction with least error and finally this neural network could be an important tool for short term load forecasting.

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