Journal of Engineering Science and Technology
Vol. 7, No. 4 (2012) 498 - 504

LOAD FORECASTING FOR POWER SYSTEM PLANNING AND OPERATION USING ARTIFICIAL NEURAL NETWORK AT AL BATINAH REGION OMAN

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Abstract

Load forecasting is essential part for the power system planning and operation. In this paper the modeling and design of artificial neural network for load forecasting is carried out in a particular region of Oman. Neural network approach helps to reduce the problem associated with conventional method and has the advantage of learning directly from the historical data. The neural network here uses data such as past load; weather information like humidity and temperatures. Once the neural network is trained for the past set of data it can give a prediction of future load. This reduces the capital investment reducing the equipments to be installed. The actual data are taken from the Mazoon Electrical Company, Oman. The data of load for the year 2007, 2008 and 2009 are collected for a particular region called Al Batinah in Oman and trained using neural networks to forecast the future. The main objective is to forecast the amount of electricity needed for better load distribution in the areas of this region in Oman. The load forecasting is done for the year 2010 and is validated for the accuracy.

Keywords: Load forecasting, Neural network, Power system, Back propagation, Energy consumption.

1. Introduction

There is a growing tendency towards unbundling the electricity system. This is continually confronting the different sectors of the industry (generation, transmission, and distribution) with increasing demand on planning management and operations of the network. The operation and planning of a power utility company requires an adequate model for electric power load forecasting. Load forecasting plays a key role in helping an electric utility to make important decisions on power, load switching, voltage control, network reconfiguration, and infrastructure development.

Nomenclatures

E	Network error
I_B	Input signal of unit B
n	Number of neurons
W_{nB}	Weight connecting neuron n to neuron B
W_{AB}	Weight Connecting neuron A to neuron B
X_1	Input 1 to neural network
X_2	Input 2 to neural network
y	Output from the neural network
Greek Symbols	
η	Learning rate parameter

Electric load forecasting is the process used to forecast future electric load, given historical load and weather information and current and forecasted weather information. In the past few decades, several models have been developed to forecast electric load more accurately. Load forecasting can be divided into three major categories: Long-term electric load forecasting, used to supply electric utility company management with prediction of future needs for expansion, equipment purchases, or staff hiring Medium-term forecasting, used for the purpose of scheduling fuel supplies and unit maintenance Short-term forecasting, used to supply necessary information for the system management of day-to-day operations and unit commitment [1, 2].

The use of artificial neural networks (ANN or simply NN) has been a widely studied electric load forecasting technique since 1990. Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting. The outputs of an artificial neural network are some linear or nonlinear mathematical function of its inputs. The inputs may be the outputs of other network elements as well as actual network inputs. In practice network elements are arranged in a relatively small number of connected layers of elements between network inputs and outputs. Feedback paths are sometimes used. In applying a neural network to electric load forecasting, one must select one of a number of architectures (e.g., Hopfield, back propagation, Boltzmann machine), the number and connectivity of layers and elements, use of bi-directional or uni-directional links, and the number format (e.g., binary or continuous) to be used by inputs and outputs, and internally [3]. The most popular artificial neural network architecture for electric load forecasting is back propagation [4]. Back propagation neural networks use continuously valued functions and supervised learning. That is, under supervised learning, the actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to desired outputs (such as historical electric loads) in a pre-operational 'training session' [5].

2. Neural Network

A neural network is a concept in computing which is used to get the mathematical model and the concept is similar to the structure and operation of the brain. It consists of a number of simple processing units 'cells' or 'nodes' connected together into a layered net-like structure. When a given set of cells (the inputs) are stimulated, the signals are passed through the network from node to node and finally exit the network through another set of simplified nodes (the outputs) [6]. The computational elements or nodes in the hidden and output layers are generally nonlinear. The simple node sums '*N*' weighted inputs are multiplied with a weight of neural network and then is passed through the tanh activation function. This is commonly used in training the non linear function. The node is characterized by an internal threshold or bias and by the type of non-linearity. There are three common types of non-linearities: hard limiters, threshold logic elements and sigmoidal nonlinearities. More complex nodes may include temporal integration or other types of time dependencies and more complex mathematical operations than summation [7]. Neural network models are characterized by the network topology, node characteristics, and training or learning rules. These rules specify an initial set of weights and indicate how weights should be adapted during use to improve performance [8, 9].

The most commonly used type of neural network is the Multi-Layered Perceptron (MLP) network MLPs are widely used as modelling tools and have been successfully applied for the prediction and modelling of multi-variable non-linear systems. It has been claimed by many researchers that a MLP network with a single hidden layer can approximate any non-linear function with arbitrary accuracy. Figure 1 shows a three-layer perceptron with one layer of hidden units. In this the first one is the input layer, second the hidden layer and third the output layer. For MLP networks, training is normally achieved through back-propagation learning. Supervised learning involves comparing the output of a network exposed to specific input with the desired output and changing the weights of the network to achieve a proper mapping. This is done by first stimulating the input nodes with a specific pattern and letting the network propagate this input through the layers [10, 11]. The output of the network is then compared to the desired output (i.e., the output expected for that particular input pattern). The error is then back-propagated through the network, changing the internal weights along the way to produce a better match between the network predictions and the "real" data [12]. To facilitate this process a number of techniques can be used which include the *delta-rule* method.

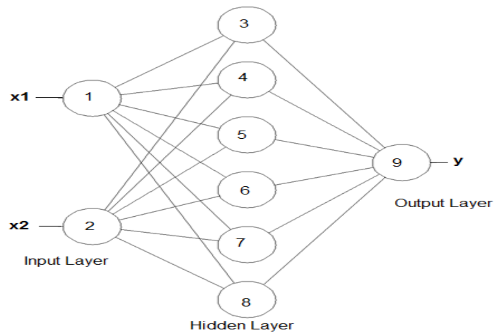

Fig. 1. A Three Layer Neural Network.

3. Back Propagation Algorithm

The objective of supervised training is to adjust the weights so that the difference between the network output *Pred* and the required output *Req* is reduced [13, 14].

This requires an algorithm that reduces the absolute error, which is the same as reducing the squared error, where

Network Error = $Pred - Req = E$ (1)

These outputs are multiplied by the respective weights ($W_{IB}...W_{nB}$), where W_{nB} is the weight connecting neuron n to neuron B. For the purpose of this illustration, let neuron 1 be called neuron A and then consider the weight W_{AB} connecting the two neurons. The approximation used for the weight change is given by the delta rule:

$$W_{AB(new)} = W_{AB(old)} - \eta \frac{\partial E^2}{\partial W_{AB}} \quad (2)$$

where η is the learning rate parameter, which determines the rate of learning, $\frac{\partial E^2}{\partial W_{AB}}$ is the sensitivity of the error, E^2, to the weight W_{AB} and determines the direction of search in weight space for the new weight $W_{AB(new)}$.

In order to minimise E^2 the delta rule gives the direction of weight change required. From the chain rule,

$$\frac{\partial E^2}{\partial W_{AB}} = \frac{\partial E^2}{\partial I_B} - \frac{\partial I_B}{\partial W_{AB}} = O_A \quad (3)$$

since the rest of the inputs to neuron B have no dependency on the weight W_{AB}.

$$W_{AB(new)} = W_{AB(old)} - \eta \frac{\partial E^2}{\partial I_B} O_A \quad (4)$$

and the weight change of W_{AB} depends on the sensitivity of the squared error, E^2, to the input, I_B, of unit B and on the input signal O_A [14].

So to summarize the process of back propagation:

- A pattern is presented to the network (i.e., the input values)
- The input is propagated through the network to give an output
- The actual output is compared with the desired output and an error function is defined (that we have to minimise)
- The errors are propagated back though the network to determine the amount by which to update the weights
- Update the weights
- Repeat this process for each pattern (when all patterns have been used we say one epoch has been completed)
- Continue until for one epoch, all outputs for each pattern are within the tolerance.
- Then we can say the network is trained and can be tried on test data.

4. Methodology

Table 1 shows the average load for the corresponding humidity and the temperature. The data of the average temperature, average load, and average humidity for the year 2007, 2008, and 2009 are fed as input to the neural networks and trained for the future prediction. Here Back propagation algorithm is used to train the network. The average temperature and humidity were taken as the inputs and the average load is taken as the outputs. The BP algorithm is used to train the network and creates the matrix which can be used for the new set of inputs. The forecasted weather is collected from the metrology department and is fed to ANN to get the predicted load for the following year. In this present study the data were collected for the year 2007, 2008, and 2009 and used to get the predicted output for the year 2010.

Table 1. Humidity, Temperature, Load Data for Al Batinah Region.

Area	Load			Temperature			Humidity		
	Max.	Min.	Avrg.	Max.	Min.	Avrg.	Max.	Min.	Avrg.
South Bathinah (Oman) 2009	158.05	49.35	103.7	30	13	21.5	100	28	64
	201.55	68.6	135.075	37	15	26	100	25	62.5
	256.65	91.6	174.125	39	16	27.5	100	13	56.5
	338.2	103.15	220.675	42	18	30	100	13	56.5
	438.55	155.4	296.975	49	25	37	96	9	52.5
	446.45	184.75	315.6	47	28	37.5	96	9	52.5
	468.4	246.55	357.475	47	29	38	98	20	59
	456.3	211.1	333.7	47	28	37.5	100	16	58
	391.3	194.7	293	44	27	35.5	100	22	61
	347.35	164.25	255.8	41	23	32	99	13	56
	260	92.4	176.2	37	18	27.5	97	16	56.5
	180.15	61.75	120.95	31	18	24.5	100	21	60.5
South Bathinah (Oman) 2008	170.15	43.3	106.725	29	13	21	98	28	63
	134.85	33.6	84.225	36	11	23.5	88	18	53
	219.15	67	143.075	38	17	27.5	99	8	53.5
	305	112.85	208.925	43	21	32	94	9	51.5
	400.9	132.15	266.525	45	23	34	95	9	52
	406.65	185.7	296.175	48	29	38.5	92	9	50.5
	394.1	146.1	270.1	45	27	36	94	8	51
	383.95	90.35	237.15	46	25	35.5	98	25	61.5
	392.65	163.45	278.05	44	26	35	99	15	57
	356.8	155.25	256.025	41	24	32.5	93	14	53.5
	255.3	78.6	166.95	35	18	26.5	94	21	57.5
	161.35	57.8	109.575	30	14	22	99	39	69
South Bathinah (Oman)2007	143.8	49.5	96.65	30	12	21	89	25	57
	135.2	54.7	94.95	36	16	26	94	17	55.5
	176.4	55.3	115.85	36	17	26.5	95	10	52.5
	295.3	103.9	199.6	42	16	29	95	10	52.5
	336.5	159.1	247.8	44	26	35	88	7	47.5
	347.3	38.6	192.95	46	24	35	98	15	56.5
	341.1	176.7	258.9	46	28	37	98	16	57
	327.1	167.7	247.4	45	27	36	92	20	56
	319.2	136.8	228	43	25	34	98	11	54.5
	252.4	94	173.2	38	20	29	98	12	55
	193.7	49.3	121.5	61	18	39.5	94	22	58
	139.7	53.6	96.65	33	16	24.5	89	33	61

5. Results and Discussion

Figure 2 shows the training carried out by the ANN. The program is done in MATLAB for thousand iterations and it indicated that the error converges to three which means that there can be a tolerance of ±3 MW error in the predicted output for 2010. It has been observed continues for thousand iterations.

Figure 3 shows the load curve. The blue, red and green curve shows the load curve for 2007 followed by 2008 and 2009 which keeps on increasing. The peak load for the year 2007, 2008 and 2009 are 260 MW, 290 MW and 340 MW respectively. The bigger curve in pink indicates the actual data collected for the year 2010 and the dark blue line indicates the predicted load curve for the year 2010. It is also observed Neural network results that the peak load could reach 360 MW by 2010 and it has also been observed that the actual data taken during 2010 has reached the peak load of 350 MW which is very near to the predicted value.

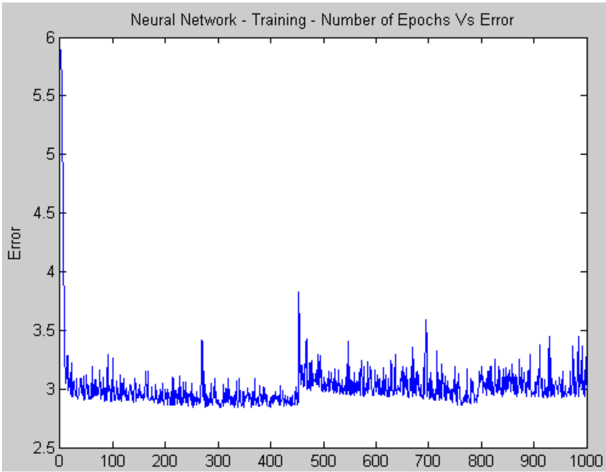

Fig. 2. Number of Epochs vs. Error (NN Training).

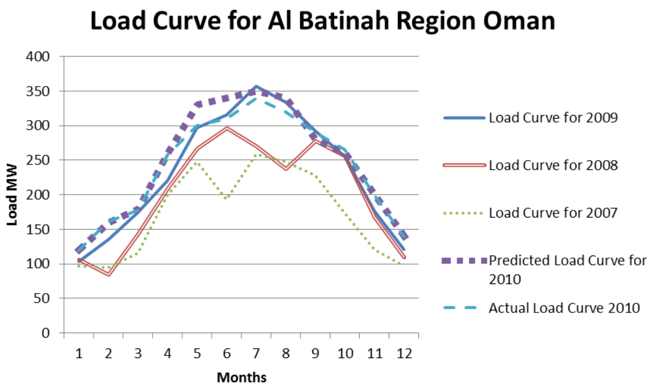

Fig. 3. Load Cure for Years 2007, 2008 and 2009,
Predicted Curve and Actual Curve for Year 2010 for Validation.

6. Conclusions

The result of MLP network model used for LONG short term load forecast for the Al Batinah region in Oman shows that MLP network has a good performance and reasonable prediction accuracy was achieved for this model. Its forecasting reliabilities were evaluated by computing the mean absolute error between the exact and predicted values. We were able to obtain an Absolute Mean Error (AME) of 2.64% which represents a high degree of accuracy. 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 long term load forecasting.

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