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Forecasting the Daily Peak Load Using Artificial Neural Networks

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Abstract

As far as electrical power system is concerned, there has been a need to find out the future load in advance. Load forecasting has been a central integral process, throughout planning and operation of electrical utilities.

An approach of artificial neural networks (multi layer perceptron) to short term load forecasting is presented in this work. Four different architectures of neural networks have been trained and tested to forecast the daily peak load of Baghdad city. A historical daily peak load and weather data were proposed for the forecasting process. A back propagation algorithm has been used to train these networks. MATLAB version 6.1 program was used.

Keywords: Short-term , Peak Load , Artificial Neural Network.

توقع حمل الذروة اليومي باستخدام الشبكات العصبية الاصطناعية

الخلاصة

إن منظومات القدرة الكهربائية بحاجة لمعرفة مستقبل الحمل لاطول فترة ممكنة.و ان توقع الحمل يعد من العمليات المهمة المكملة لأنظمة تخطيط و عمل منظومات القدرة.

تم في هذا البحث استخدام طريقة الشبكات العصبية الاصطناعية (Artificial Neural Networks) المتعددة الطبقات في التوقع قصير الأمد. فقد أعدت اربعة شبكات عصبية مختلفة لتوقع حمل الذروة اليومي لمدينة بغداد و تم تدريبها و اختبارها لهذا الغرض. و استخدمت قيم أحمال الذروة و درجات الحرارة العظمى لسنوات ماضية كمعطيات للشبكة لكي تقوم بعملية التوقع من خلال استخدام خوارزمية الانتشار الرجعي للخطأ (Backpropagation Algorithm) في تعليم الشبكات الثلاث و استخدمت لغة MATLAB version 6.1 في بناء البرامج المعدة.

1 Introduction

In order to supply high quality electric energy to the customer in a secure and economic manner, an electric company faces many economical and technical problems in operation, planning and control of an electric energy system [1].

Load forecasting is one of the central functions in power system operation [2].

The different types of load forecasting can be classified according to the forecasting period as: short term, medium term, and long term forecasting [1, 3, 4].

Much has been written on the subject of load forecasting and neural network.

-Lee K.Y, et. al. , 1992:

In [1], the paper proposes artificial neural network (ANN) method to forecast the short term load forecasting (STLF) for a large power system. Inputs to ANN are the past load and the output is the next day 24

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hours. Two methods have been produced. The average percentage error was about 2%. Backpropagation algorithm (BPA) was used for training the network. Note that the weather variables were not included.

-Ribeiro L. S., et.al., 1996:

In [5], the paper proposes a study of the application of ANN in the area of very short-term load forecasting (ten-minute intervals). A load history series of Minas Gerais Power Plant, Brazil. A backpropagation network with momentum and with adaptive learning rate was trained for each day of the week. The average means error about 2.56% for multi step procedure. Weather variables were not included.

- Carpinteiro O. A., et. al. , 2001:

In [6], the paper proposes a novel neural model to the problem of STLF. The neural model was made up of two self-organization map nets; one on top of the other. It has been successfully applied to domain in which the context information given by former events plays a primary role. The results obtained have shown that hierarchical neural model (HNM) average percentage error was 2.33%. Weather effect was not included.

2 Artificial Neural Network:

An artificial neural network(ANN) is a computational system inspired by the functioning of human brain. The system is made up of highly interconnected processing elements. The artificial neuron is a simplified mathematical representation of the biological neuron, which execute the sum of weighted input through the weights associated to those inputs (synaptic weights), then it applied a function to the result in order to generate the output. The function which applied to the result is called activation function (sigmoid), a feature which enables the ANN to represent more complex problem.

The architecture or topology of a neural network is formed by an input layer, an output layer and one or more hidden layers. The choice of the number of hidden layer and number of the processing elements in each layer is directly related to the problem at hand.

In mathematical term [7] :

$$y_k = f(\sum_{i=1}^{n} W_{ki} x_i) \qquad .....(1)$$

$f(x)$: is the activation function

w_{ki} : synaptic weight

x_i : input signal

ANN knowledge is stored in the synaptic weight of each link between two processors. By means of learning algorithm [5].

The network weight in such a way that the network output error is minimized.

The typical operation of ANN can be classified into two stages (a) training stage (b) recall stage. The training stage is conducted by using various training data set which include the respective inputs and the corresponding desired output. The initial network connection weights are set equal small random numbers.

After the network is properly trained, the recall stage will start. In this stage, a set of test data is applied to the network. After ward, the performance of the network is analyzed. This performance depends on various factors such as: the statically soundness of training data set, the structure and the size of the network, initial network weights, learning strategy and input variables, selecting the momentum and learning rate values, etc [8].

3 Case Study:

The problem under study is to calculate the forecasted daily peak demand loads for the next day of city of Baghdad. Historical data for peak loads demand and maximum of temperature values for many areas of Iraq for previous months were used.

Fig.(1) shows the historical peak loads that have been used in training and testing process.

Figs. (2), (3) , and (4) shows the historical data for temperature used in training and testing process for the three different areas in Iraq (north, middle, and south).

Several experiments were performed for choosing the ANN architectures and the organization of input vectors. More details are given in section four. Backpropagation algorithm with random initialization of weights was used for ANN multilayer percrptron training.

A qualitative analysis of load forecasting problem indicates that the following variables influence the load demand: weather effect (temperature, humidity, season), type of day of the week, and unexpected events (machine break down or disturbance, each person behave on his individual way) [9].

4 Peak Load Forecasting Models:

In this work neural network structures have been built and tested to forecast the daily peak load, to give the target output.

The structure divided the year in to four networks according to the season's (winter, spring, summer, and autumn). The seasons are classified according to the values of peak loads over the year. The training and testing sets are the data over a period of one whole year.

The network information of the structures is shown in Table (1) and Table (2). The structure of winter, spring, and summer networks are the same, but the structure of autumn network is different.

The input parameters to structure contain the forecasted maximum temperature in three areas of Iraq, for the day load forecast being conducted. The recorded maximum temperature of previous day in the three areas, and the recorded maximum temperature and peak load in the past ten days with the same load pattern like the forecasted day.

We have used the normalized equation to normalize the input and output vectors for the load values and temperature values:

$$X_{nor} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad \ldots(2)$$

Where,

X_{nor} : normalized value

x_{min} : minimum value

x_{max} : maximum value

Different values of momentum and learning rate have been selected for the four networks as shown in tables (1) and (2). The value of SSE shown depends on the accuracy of the target output of the leaning process. In the four structures, there is no particular treatment for holidays, and the special days have been excluded from the training sets.

The abnormal data must be recognized in order to remove them from the training sets.

5 Results and Discussion:

The results of forecasting peak load for the four MLP networks of the structures were tested.

Testing would require the use of data at all seasons of the year, but the testing must not be carried with the same data used in the networks training.

The testing results of the four networks including actual and forecasted peak load values and the percentage error are shown in Tables (3), (4), (5), and (6).

The criterion for our work was determining of the average percentage error for the forecasting values. This is defined in eq.(3):

$$Error = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{\hat{L}_i - L_i}{L_i}\right]\times 100\% \quad ..(3)$$

N : Number of cases to be forecasted.

$\hat{L}_i$: the ith load forecasted value.

L_i : the ith load value.

Table (7) shows the final average percentage error for the whole program for all seasons.

The average percentage error is (1.02)% , which indicate that including the temperature to the input vector and dividing the year in to seasons make the accuracy of forecasting better. So the structure of artificial neural networks has an effect on the results. It uses two hidden layer , the second hidden layer filter the output , This paper reaches an accurate forecasting over the historical studies.

6 Conclusion:

Short term load forecasting is an essential component in the operation of electric utilities. This paper demonstrates how neural network can be used successfully to solve STLF problem by forecasting the daily peak load of Baghdad city. The effects of learning rate and momentum on the efficiency of convensil learning algorithm have been devoted to speed up learning process. It is found that accurate load forecasting results with error of 1.02% (by including load and temperature values to the input vector that used to train the network and dividing the year in to four seasons), can achieved by the neural network in a very efficient way.

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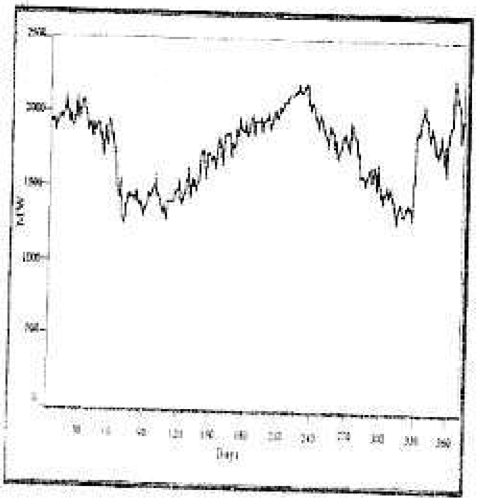

Fig.(1) The peak loads data

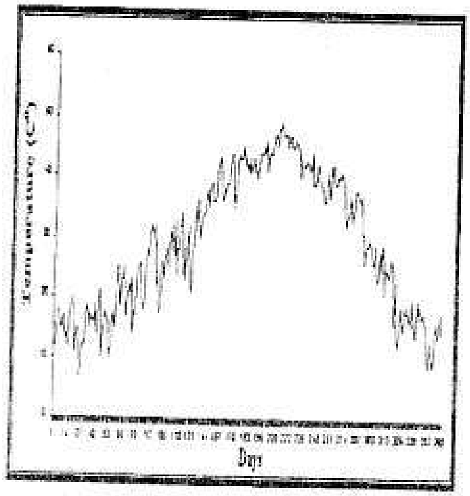

Fig.(2) The temperature values for the north region

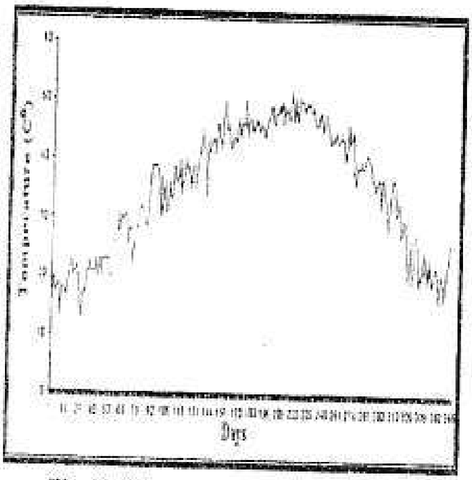

Fig.(4) The temperature values for the south region

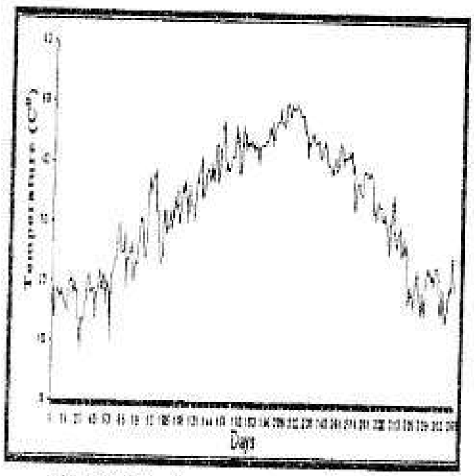

Fig.(3) The temperature values for the middle region

Table(1) The networks information of Winter, spring, and summer.

No.	Item	Winter	Spring	Summer
1	Pattern vectors no.	26	20	64
2	Layer no.	4	4	4
3	No. of neurons in input layer	46	46	46
4	No. of neurons in 1'st hidden layer	23	23	23
5	No. of neurons in 2'nd hidden layer	12	12	12
6	No. of neurons in output layer	1	1	1
7	Learning rate	0.089	0.132	0.0142
8	Momentum	0.75	0.75	0.75
9	SSE	0.001	0.002	0.01
10	No. of iterations	3264	826	40038

Table(2) The networks information of autumn.

No.	Item	Autumn
1	Pattern vectors no.	31
2	Layer no.	4
3	No. of neurons in input layer	46
4	No. of neurons in 1'st hidden layer	27
5	No. of neurons in 2'nd hidden layer	16
6	No. of neurons in output layer	1
7	Learning rate	0.0053
8	Momentum	0.75
9	SSE	0.001
10	No. of iterations	20667

Table (3) The testing results for winter network

No.	Day/Month	Actual	Forecasted	error
1	2/12	1821	1831	0.6
2	3/12	1829	1840	0.6
3	7/12	1848	1838	0.5
4	8/12	1850	1817	1.7
5	13/12	1871	1858	0.6
6	14/12	1979	1944	1.7
7	24/12	2041	1995	2.2
8	2/1	1940	1977	1.9
9	10/1	1950	1898	2.6
10	14/1	1960	1941	0.9
11	17/1	1965	1933	1.6
12	22/1	1976	1967	0.4
13	29/1	2008	2000	0.3
14	3/2	1990	2026	1.8
15	5/2	1980	1988	0.4
16	6/2	1979	1946	1.6
17	15/2	1885	1897	0.3
18	18/2	1870	1894	1.2
19	22/2	1963	1919	2.2
20	27/2	1746	1745	0.05

Table (4) The testing results for spring network

No.	Day/Month	Actual	Forecasted	error
1	5/3	1432	1429	0.2
2	11/3	1437	1449	0.8
3	13/3	1436	1420	1.1
4	16/3	1428	1425	0.2
5	19/3	1431	1422	0.6
6	21/3	1434	1427	0.4
7	24/3	1438	1422	1.1
8	28/3	1446	1434	0.7
9	29/3	1440	1446	0.4
10	2/4	1470	1446	1.6
11	4/4	1432	1457	1.7
12	9/4	1415	1411	0.2
13	11/4	1408	1426	1.2
14	14/4	1397	1416	1.3
15	16/4	1407	1422	1.0
16	19/4	1400	1416	1.1
17	21/4	1410	1446	2.4
18	25/4	1444	1444	0
19	27/4	1409	1426	0.9
20	29/4	1460	1455	0.3

Table (5) The testing results for summer network.

No.	Day/Month	Actual	Forecasted	error
1	3/5	1540	1548	0.5
2	6/5	1555	1534	1.3
3	26/5	1756	1757	0.1
4	6/6	1818	1824	0.3
5	18/6	1861	1867	0.3
6	21/6	1880	1889	0.4
7	28/6	1932	1946	0.6
8	1/7	1942	1978	1.8
9	18/7	1970	1939	1.5
10	21/7	2017	2043	1.2
11	24/7	2056	2065	0.4
12	28/7	2096	2041	2.5
13	1/8	2135	2142	0.3
14	22/8	1979	2008	1.4
15	27/8	1950	1932	0.9
16	2/9	1850	1867	0.9
17	8/9	1830	1813	0.9
18	15/9	1772	1718	2.9
19	16/9	1768	1778	0.5
20	27/9	1709	1712	0.1

Table (6) The testing results for autumn network.

No.	Day/Month	Actual	Forecasted	error
1	2/10	1580	1560	1.2
2	4/10	1560	1590	1.9
3	5/10	1549	1584	2.2
4	7/10	1543	1544	0.06
5	9/10	1537	1547	0.6
6	11/10	1521	1532	0.7
7	12/10	1519	1496	1.5
8	16/10	1506	1522	1.0
9	22/10	1482	1475	0.4
10	25/10	1456	1461	0.3
11	28/10	1436	1446	0.6
12	1/11	1323	1331	0.6
13	3/11	1336	1344	0.6
14	9/11	1388	1404	1.1
15	18/11	1474	1448	1.7
16	22/11	1606	1590	0.9
17	25/11	1692	1692	0
18	27/11	1725	1715	0.5
19	29/11	1800	1778	1.7
20	30/11	1812	1801	0.6

Table (7) The final percentage error for the four programs.

seasons	Average percentage error
Winter	1.4
Spring	0.86
Summer	0.94
Autumn	0.908