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Short Term Electric Load Forecasting based on Artificial Neural Networks for Weekends of Baghdad Power Grid

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ABSTRACT
This work presents proposed methodsfor short term power load forecasting (STPLF) for the governorate of Baghdad using two different models of Artificial Neural Networks (ANNs). The two models used in this work are the multi-layer perceptron (MLP) model trained with Levenberg-Marquardt Back Propagation (BP) algorithm and Radial Basis Function (RBF) neural network. Inputs to the ANN are thepast loadsvalues and the output of the ANN is the load forecast for the weekends of certain months for Baghdad governorate. The data is divided into two parts where half of them was used for training and the other half was used for testing the ANN. Simulations were achieved by MATLAB software with the aid of Neural networks toolbox, where the data obtained for the Iraqi national grid were rearranged and preprocessed. Finally, the simulations results showed that the forecasted load values for the Baghdad governorate by the proposed methods were very close to actual ones as compared with the traditional methods.

General Terms
Load demand, neural networks, load prediction, artificial intelligence, energy consumption.

Keywords
Load forecasting, multilayer perceptron, radial basis neural networks (RBF), Back Propagation.

1. INTRODUCTION
Power load forecasting (PLF) accurately plays a very important role for electric utilities in a competitive environment created by the electric industry deregulation. An electric company is confronted with many economical and technical problems in operation, planning and control of an electric energy system since customers require high quality electric energy to be supplied in a secure and economic manner [1]. PLF helps an electric utility by making important decisions on generating, interchanging, and purchasing electric power, load switching, and infrastructure development. Besides PLF is crucial for energy suppliers, financial institutions, and others involved in electric energy generations, transmission, distribution, and markets [2]. Moreover, PLF is playing a key role in reducing the generation cost, it is also essential to the reliability of power systems. The system operators use the load forecasting result as a basis of off-line network analysis to determine if the system might be vulnerable. If so, corrective actions should be prepared, such as load shedding, power purchases and bringing peaking units on line [3]. According to forecasting time period, PLF can be divided into three categories [4]: Short Term Power Load Forecast (STPLF) which is usually from one hour to one week, and it is primarily used for the day-to-day operation, control and scheduling of the power systems. Medium Term Power Load Forecast (MTPLF) which is usually from a week to a year and it is generally used for the maintenance and scheduling programs of fuel supplies. Finally, Long Term Power Load Forecast (LTPLF) which is longer than a year and it is primarily used for power system development planning. Many researchers have investigated power load forecasting;in [5] the authors presented a multi-layer feed-forward neural network model with the aim to compare the forecasting accuracy of a time-series and an ANN-based model. While researchers in [6] used a three layer feed-forward neural network and a back-propagation training algorithm, so that electricity prices could be considered as one of the main factors affecting the load in deregulated markets. A supervised neural network-based model has been proposed by [7] to forecast the load in the Nigerian power system. [8] Proposed a study of design a neural network model called Elman recurrent network by using MATLAB software to simulate the power load forecasting. The research presented by [9] suggested Models based on the so-called Multi- Layer Perceptron (MLP) network to solve the problem of short term load forecasting. Finally, [10] presented a new method for STPLF to predict the demand in the future. The main objective of this study was to analyze the profile or pattern of the forecasted load and to predict the load demand during weekends. [11] Proposed a multi-parameter regressionmethod for forecasting which has error within tolerable range.Particle swarm optimization has been applied on STPLF in [12], while [13] used a new approach for short-term load forecasting (STLF), where curve fitting prediction and time series models are used for hourly loads forecasting of the week days combined with genetic algorithm.

2. ARTIFICIAL NEURAL NETWORKS
Artificial Neural Networks (ANNs) are a data processing system consisting of a large number of simple, highly interconnected processing elements inspired by the biological system and designed to simulate neurological processing ability of human brain [14]. A generic artificial neural network can be defined as a computational system consisting of a set of highly interconnected processing elements, called neurons, which process information as a response to external stimuli. An artificial neuron is a simplistic representation that emulates the signal integration and threshold firing behavior of biological neurons by means of mathematical equations [15]. An artificial neuron and its model is shown in Figure 1.

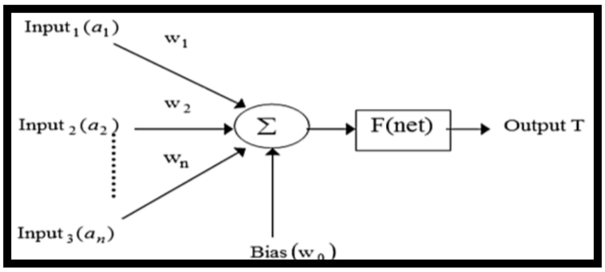

Fig. 1: The basic model of an artificial neuron.

3. PROPOSED MLP AND RBF ANN MODELS FOR STPLF

In this section, models of MLP and RBF are presented to forecast the output load of weekends for certain months in 2012 for Baghdad City asa case study. The proposed structure for predicting demands consisted of four inputs for training and one output.

3.1 Designing MLP and RBF ANN models for STPLF

MLP is a popular architecture of ANN andcan be used for STPLF. In this work, MLP has been trained with Levenberg - Marquardt BP algorithm and the transfer function within the network was the sigmoid nonlinear activation function with only one neuron in its output layer as shown in figure 2. This neuron gave the output value, which contains the predicted value of the weekend load.

The second type of ANN model used in this work to solve the problem of STPLF was RBF neural network model. RBF model consists of three layers. The input layer has neurons with a linear function and the hidden neurons are processing units that perform the RBF function. The output neuron is a summing unit to produce the output as a weighted sum of the hidden layer outputs, figure 3 depicts the proposed model of the FBF NN structure.

Selecting the basis function is not crucial to the performance of the network; the most common is the Gaussian basis function, whichis used in this study. Designing ANN models follow a number of systemic procedures. In general, there are five basic steps:-

1. **Collecting Data:** Collecting and preparing data is the first step in designing ANN models. In this work, all data for Baghdad power grid have been collected from the Iraqi Operation and Control Office for 3 years from 2010 to 2012.
2. **Data Preprocessing:** After data collection, two preprocessing procedures are conducted to train the ANNs more efficiently. These procedures are: (a) solve the problem of missing data and (b) normalize data.
3. **Building the Network:** At this stage, the number of hidden layers, neurons in each layer, transfer function in each layer, training function and performance function were specified.
4. **Training the Network:** During the training process, the weights are adjusted in order to make actual outputs (forecasted) close to the target (measured) outputs of the network. MATLAB provided built-in transfer functions linear (purelin), hyperbolic tangent sigmoid (logsig) and Logistic (tansig) which were used in this work.
5. **Testing the Network:** The next step was to test the performance of the developed model. In order to evaluate the performance of ANN models such as the mean square error (MSE), MSE provided information on the STPLF performance, which is a measure of the variation of predicted values around the measured data. The lower the MSE was, the more accurate was the estimation. It can be calculated from **Eq. (1)** below:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}[L_a(n) - L_p(n)]^2 \quad (1)$$

Where $L_a(n)$ is the actual load, $L_p(n)$ is the forecasted or predicted value of load, and N is the number of data points.

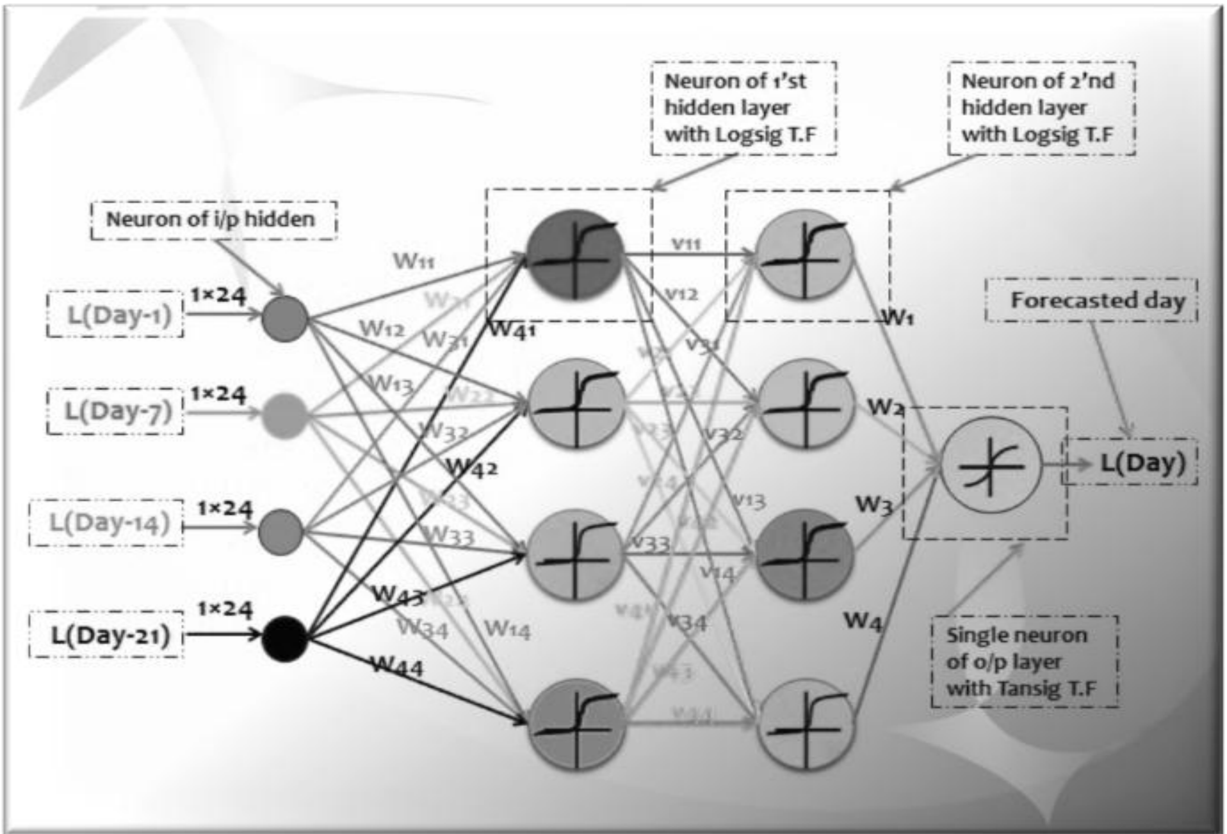

Fig. 2: The proposed structure of MLP Neural network model to forecast the weekend load.

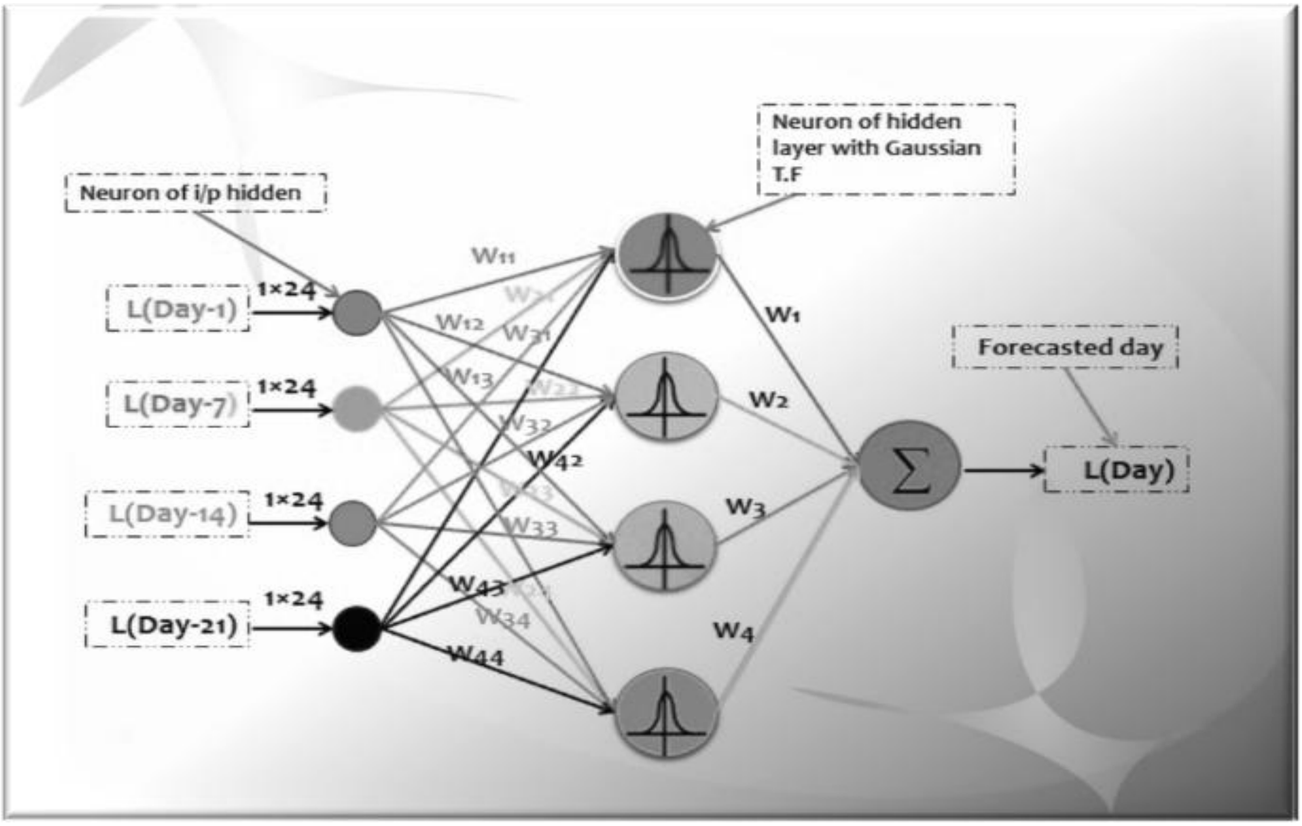

Fig. 3: The proposed structure of RBF model to forecast a weekend load.

3.2 Learning Mechanism of MLP and RBF ANN models for STPLF

The learning mechanism of MLP and RBF ANN models for STPLF can be summarized in the following steps:-

1. The program started by reading data from an excel file. The function of "xlsread" was used to read the data specified in the excel file.
2. The loaded data was normalized to remain within the range (0 - 1).The actual load was scaled using the expression represented in Eq. (2):-

$$L_s = \frac{L}{L_{max}} \quad (2)$$

Where L_s is the scaled or normalized load, $L$is the actual load in MW, andL_{max} is the maximum load during the day in MW.

3. The neural network was constructed by using the function (Newff) for MLP or by using the function (Newrb) for RBF; each of them has one input layer, one hidden layer and one output layer. The transfer functions for hidden and output layers were "tansig" and "logsig", respectively. The number of neurons in input and output layers was closely related with the sample, according to the historical data, but the number of neurons in hidden layer could be taken from the empirical formula :

$$i = \sqrt{(n + m)} + a \quad (3)$$

Where i is the number of neurons in hidden layer, n is the number of neurons in input layer, m is the number of neurons in output layer, and a is a constant and 1< a <10.

4. The network is next configured as follows:

   net.trainFcn = LM;

   net.trainparam.min_grad = 0.00000001;

   net.trainParam.epochs = 1000;

   net.trainParam.lr = 0.25;

   net.trainParam.mc = 0.8;

   net.trainParam.max_fail =50;

Where trainFcn" defines the function used to train the network. It can be set to the name of any Training function (LM ='trainlm';Levenberg-Marquardt BP), "trainparam.min_grad" denotes the minimum performance gradient, "trainParam.epochs" denotes the maximum number of epochs to train, "train Param.lr" denotes the learning rate, "trainParam.mc"denotes the Momentum term,"trainParam.max_fail" denotes the maximum validation failures.

5. The network was trained with previous data by using supervised Levenberg -Marquardt BP algorithm. In this study, the data was from (2010) to (2011) for training.
6. The network was simulated or tested after completing its training. This process is achieved by calling the function "sim".

7. The output from the constructed network was de-normalized in order to compare it with the measured data and then the results were written in excel file.

8. The last step was performed by calling the performance function to calculate and store the performance error statistics like MSE. Fig. 4 shows the programming of MLP and RBF models using MATLAB.

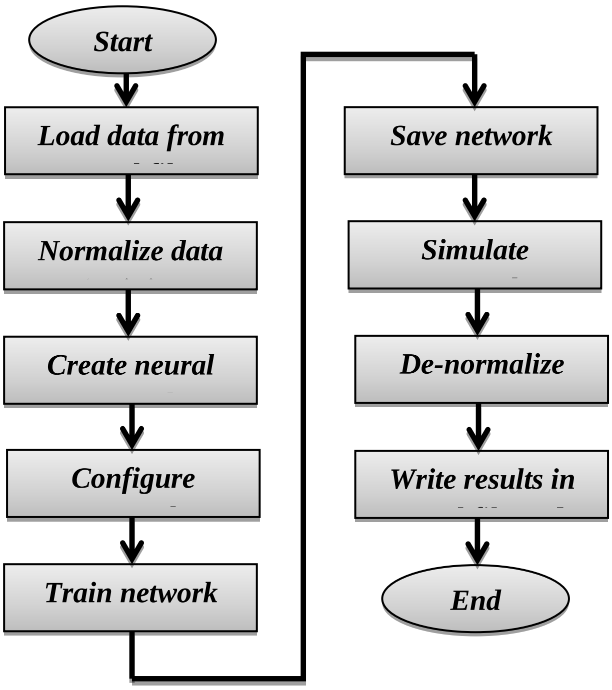

Fig. 4: Flow chart for programming MLP and RBF Models using MATLAB.

4. SIMULATION RESUTS

In this section, the simulations on the proposed models of MLP and RBF are presented to forecast the output load of the weekends for certain months in 2012 for Baghdad governorate as a case study. The proposed structure for predicting demands consisted of four inputs for training and one output. Figure5 shows the relationship between loads in (MW) and time in (hrs) for Sat. 28/Jan./2012 for Baghdad city. As can been seen from the figure that the predicted load values using RBF is closer to the actual loads than that of the MLP. Tables1 and 2 show the training and testing data for forecasting a weekend of Saturday in July 2012 for Baghdad city respectively. Whereas Table 3 presents the actual and predicted load values using MLP and RBF models. Figure 6 shows that the predicted loads using RBF and MLP models to forecast the load values for the weekendfor Fri 27 / July / 2012, while figure 7 is for sat 27 / Oct. / 2012. The figures show that the RBF achieves better performance than MLP over the entire weekend time. It can be seen form the figures that for certain weekend the forecasted load curves lie above the actual load curve (figure 5) while for other weekend it lie below the actual loads (figure 6). Figures 6 and 7 shows that the forecasted load values using RBF model exactly fits the actual load curve which means that RBF perform very well than MLP, still the predicted load values using MLP are good as compared with the actual load curve.which means that the results obtained using both models can be trusted and can be used for a practical power system.

Table 1. The training data for forecasting a weekend of Saturday in July 2012 for Baghdad Governorate

	Input data for training (MW)				**Target for training**
Date	**Sat, 02 Jul, 11**	**Sat, 09 Jul, 11**	**Sat, 16 Jul, 11**	**Fri, 22 Jul, 11**	**Sat, 23 Jul, 11**
1	2979	3142	3140	3112	3205
2	2882	3067	3065	3037	3127
3	2954	3142	3140	3112	3205
4	2990	3180	3178	3150	3243
5	2954	3142	3140	3112	3205
6	3080	3275	3273	3244	3340
7	3224	3408	3405	3375	3475
8	3206	3408	3405	3375	3475
9	3242	3426	3424	3394	3494
10	3278	3464	3462	3431	3533
11	3296	3483	3481	3450	3552
12	3343	3517	3515	3484	3587
13	3347	3521	3519	3487	3591
14	3347	3521	3519	3487	3591
15	3386	3597	3594	3562	3668
16	3314	3521	3519	3487	3591
17	3350	3559	3556	3525	3629
18	3386	3597	3594	3562	3668
19	3422	3635	3632	3600	3707
20	3368	3673	3670	3637	3745
21	3278	3559	3556	3460	3629
22	3170	3445	3399	3412	3514
23	3098	3290	3261	3259	3303
24	3051	3207	3205	3177	3271

Table 2. The testing data for forecasting a weekend of Saturday in July 2012 for Baghdad Governorate

	Input data for testing (MW)				Actual o/p (MW)
Date	Sat, 07 Jul, 12	Sat, 14 Jul, 12	Sat, 21 Jul, 12	Fri, 27 Jul, 12	Sat, 28 Jul, 12
1	2951	3260	3315	3320	3227
2	2825	2886	2937	2941	2858
3	2744	3052	3105	3110	3022
4	2788	3177	3231	3236	3145
5	3033	3135	3189	3194	3104
6	3399	3509	3567	3573	3473
7	3440	3592	3651	3658	3555
8	3562	3633	3693	3700	3596
9	3603	3716	3777	3784	3677
10	3725	3799	3861	3868	3759
11	3766	3841	3861	3868	3759
12	3827	3903	3924	3932	3821
13	3807	3882	3903	3911	3800
14	3807	3882	4029	4037	3923
15	3807	3882	4155	4164	4046
16	3990	4069	4176	4185	4066
17	4010	4090	4155	4164	4046
18	4010	4090	4155	4164	4046
19	4010	4090	4113	4121	4005
20	4010	4090	4071	4079	3964
21	4002	4048	4029	4037	3932
22	3888	3965	4010	4037	3923
23	3848	3922	3960	3995	3882
24	3609	3675	3725	3742	3636

Table 3. Actual output and forecasted load values for RBF and MLP for Sat. 28/July/2012

No. of hour	Predicted output using MLP(MW)	Predicted output using RBF(MW)	Actual output (MW)
1	3559.7	3388	3227
2	3039.3	2982.5	2858
3	3402	3173.9	3022
4	3584.3	3309.1	3145
5	3270.7	3241	3104
6	3694.4	3629.3	3473
7	3761	3719.4	3555
8	3871.3	3755.2	3596
9	3905.4	3844.9	3677
10	4048.9	3926.8	3759
11	4065.2	3938.4	3759
12	4128	4002.3	3821
13	4107.7	3981	3800
14	4149.7	4073.6	3923
15	4157.8	4165.5	4046
16	4272.3	4231.6	4066
17	4285.7	4222	4046
18	4285.7	4222	4046
19	4282.9	4191.6	4005
20	4276	4161.1	3964
21	4302	4116.1	3932
22	4165.6	4089.5	3923
23	4120.1	4043.7	3882
24	3907	3793.9	3636
MSE	**4.32E-03**	**1.55E-03**	

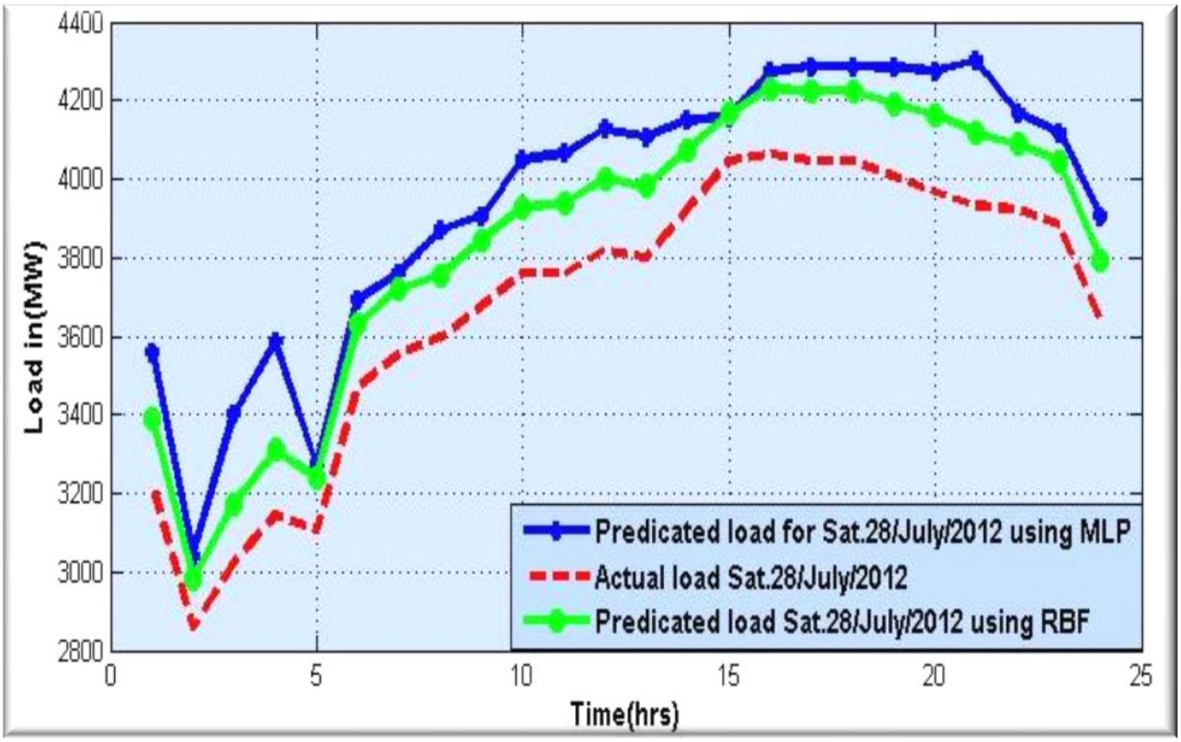

Fig. 5: Actual and predicted load using MLP and RBF for the weekend of Saturday / July / 2012 for Baghdad city.

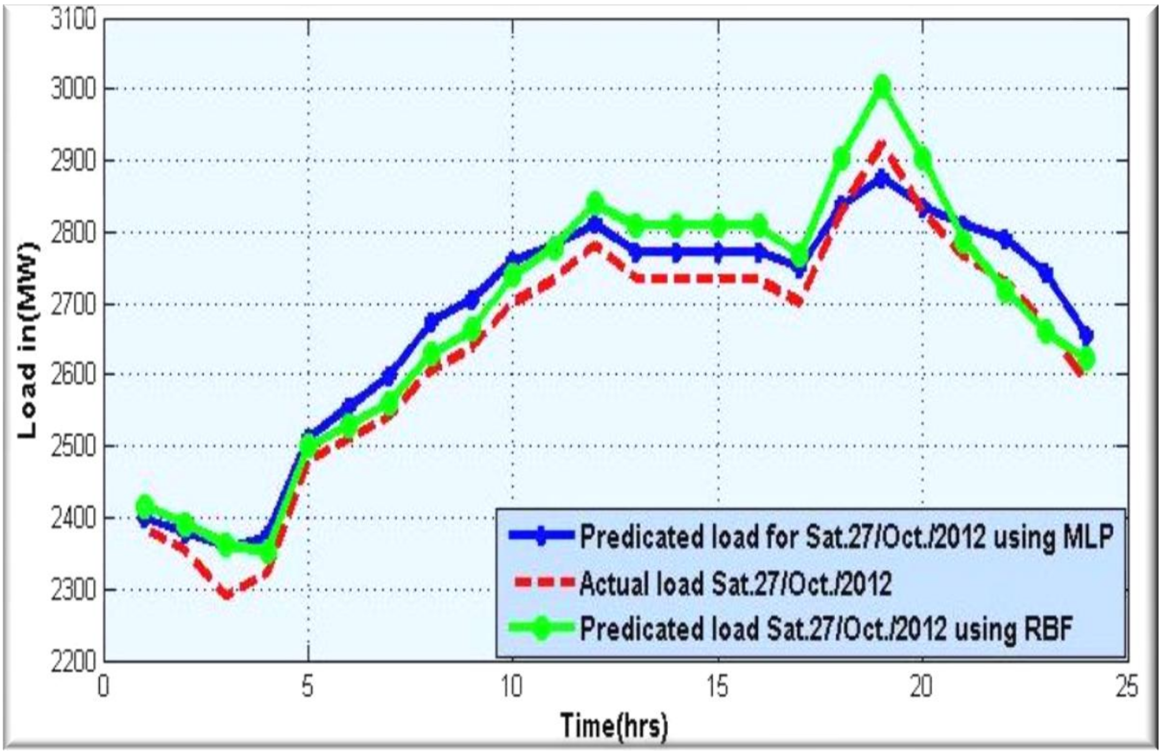

Fig. 6:Actual and predicted load using MLP and RBF of a weekend of Friday / July / 2012 for Baghdad city.

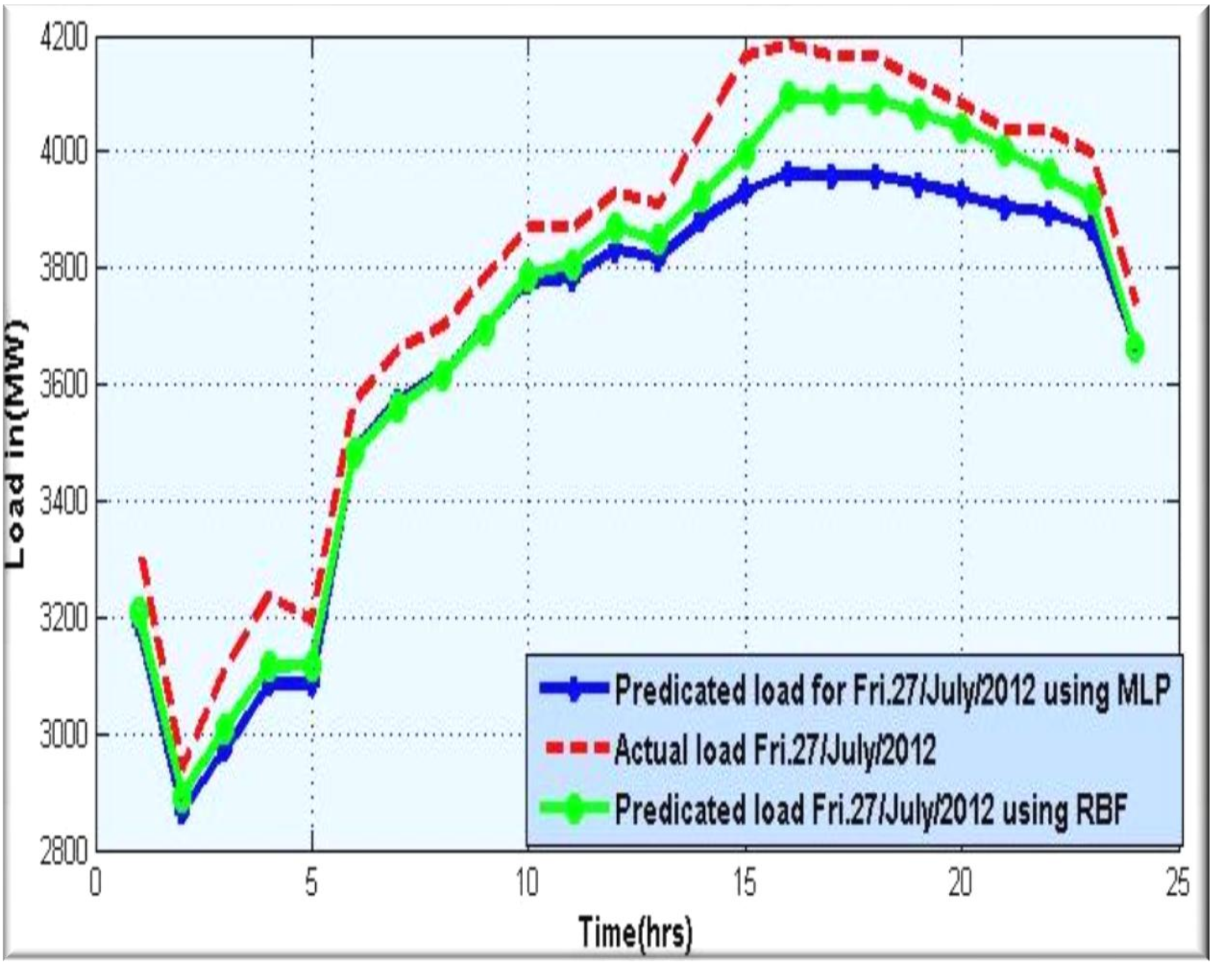

Fig. 7: Actual and predicted load using MLP and RBF of a weekend of Saturday in October 2012 for Baghdad city.

5. CONCLUSIONS

In this work, simulations and programming of short-term power load forecasting problem presented for Baghdad city power grid by using two different models of artificial neural networks, the feedforward MLP and radial basis functions RBF models. The two models presented good forecasted load values for the weekends of Baghdad city for certain months, but RBF showed very good performance as compared to MLP. The results obtained showed the effectiveness of the developed method. Based on the results obtained from this work, it can be conclude that ANN models with the developed structure could perform good prediction with least error and finally this neural network could be an important tool for short term power load forecasting.

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