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Short-Term Load Forecasting Based on NARX and Radial Basis Neural Networks Approaches for the Jordanian Power Grid

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Abstract— This paper presents two techniques for short-term load forecasting (STLF) based on Artificial Neural Networks method (ANN). These techniques are the nonlinear auto regressive with external input (NARX) and radial basis function (RBF). The results from both methods are compared in order to attain minimum percentage errors. Input data implies weather factors such as temperature and humidity. A comparison between the two techniques shows that RBF method has a better performance that NARX method in short periods training whereas NARX has the advantage in long periods training. The comparison between hourly actual and forecasted load readings shows a reasonable normalized mean square error (NMSE) with minimum values in summer: 3.9 % for NARX and 3.5% for RBF, and in winter: 3.5% for NARX and 3.47% for RBF. Results show that the minimum error is achieved by using five training days for summer and nine days for winter.

Keywords— ANN, Jordan, NARX, RBF, STLF.

I. INTRODUCTION

The STLF is a process to predict the electric load in terms of hours and days ahead. It is basically used to decide whether an extra power generation should be installed to meet the demand or not. The demand can be met by installing new generation plants or by exchanging power from neighboring countries. Load forecasting is also used to decide whether the output of the running generation units should be decreased or stopped. In order to predict the electric demand of any power system, it is important to investigate the load pattern and the factors that affect the demand [1]. In Jordan's case, a robust STLF model needs to be prepared as a first step for power system operation and planning. The previous models of STLF used by National Electric Power Company (NEPCO) in Jordan are based on growth rate technique which is not accurate and reliable; thus it is necessary to have a direct and reliable model to predict the load series in terms of hours and days. In this paper, two ANN techniques (NARX and radial basis) are employed to predict the STLF for Jordan network.

The implementation of ANN in STLF was detailed by several researchers elsewhere in the world as follows: Syed and Hawary [2] presented three advanced ANN architectures to apply STLF for Nova Costa region, in Canada; and the results are compared with Feed Forward Neural Network (FFN). The application of these architectures provides large improvements over FFN. In [3], Tee, Judith and Ellis introduced ANN approach for hourly load forecasting based on load data obtained from a previous day. Historical load data for the ISO-New England control area was used to test the proposed model. As a result, the percentage error was found to be 0.43% which is better than percentages obtained from previous models. In [4], a review study for STLF techniques and their accuracy is applied on a small scale such as office buildings based on linear and non-linear models which serve as a substantial solution for smart grid economic dispatch problem. Elias and others [5] conducted STLF for Spain based on time series and regression methods using statistical approaches and artificial intelligence methods (AI). Primitive and derived weather variables are used in their study as

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an exogenous input in addition to monthly and weakly seasonality. Inputs are investigated and used to build ANN forecasting models. Xie and others [6] presented a brief analysis for the behavior and architecture of NARX, which was tested by using a real data set based on vibration data from a CO2 compressor. NARX approach outperforms the conventional neural networks such as feed forward time delay neural network (TDNN). Xia and others [7] presented three ANN models for STLF of electric power. In their study networks were trained using historical load data and weather data that influence electric power consumption (such as wind speed, precipitation, atmospheric pressure, temperature and humidity). In order to do this, a V-shape temperature processing model is proposed.

In this paper, two techniques for STLF based on ANN are presented. These techniques are NARX and RBF which are selected for their reliability, simplicity, ability to construct nonlinear relationships between variables, high accuracy limits and low percentage error. Section two of the paper presents the input data followed by Section three which presents the methodology. Results and discussions are presented in Section four followed by conclusion. The results from both methods are presented with emphasis on the percentage error indices. The input data implies weather factors such as the temperature, and humidity. The emphasis of this paper is to show that NARX and RBF ANN techniques can be used side by side with the existing method implemented by NEPCO for both summer and winter seasons. The proposed techniques NARX and RBF provide five days forecasting with high accuracy and reasonable relative error values in the range between 0.1-3.9% as it will be seen in section 4.

II. INPUT DATA

Weather factors including temperature, humidity, pressure, wind speed and precipitation have significant effects on the energy consumption patterns in any country. However, the temperature has a significant impact on the demand response [8]-[10]. In this paper, the data used in analysis is classified into: weather and load data. The hourly metrological data (temperature and humidity) is obtained from Jordan Metrological Department for September and August 2014, whereas the hourly load data in Mega Watts (MW) is obtained from NEPCO. The relation between both temperature and humidity with load is investigated via the correlation factor, which is an index describing two sets of data linked together. It may be positive or negative. For these two sets of data (*x* and *y*), the correlation factor between *x* and *y* ($corcoef_{x,y}$) can be calculated as [11]:

$$corcoef_{x,y} = \frac{\sum_{i=1}^{n}(x_i - avg(x)) \times (y_i - avg(y))}{\sqrt{\sum_{i=1}^{n}(x_i - avg_x)^2 \times \sum_{i=1}^{n}(y_i - avg_y)^2}} \tag{1}$$

Where $corcoef_{x,y}$ is the correlation between *x* and *y*, and avg_x is the average value of *x* and is given by:

$$avg_x = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

The correlation between temperatures (in C^o) and humidity versus electric loads (in MW) for September 2014 is presented in Fig. 1 which shows the best fitted line and good correlation factors of 0.834 (load vs. temperature) and -0.766 (load vs. humidity) respectively.

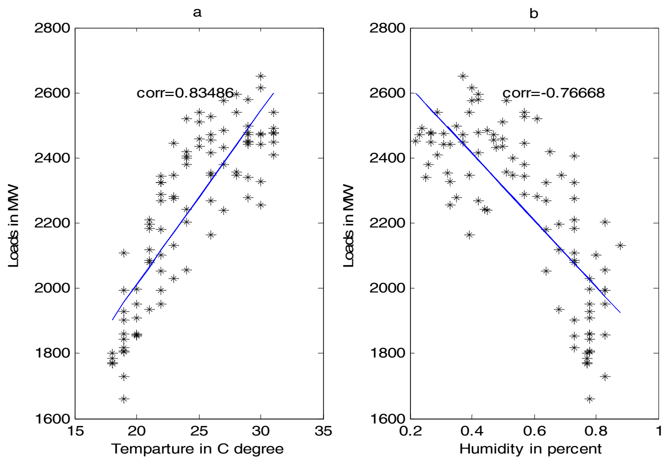

Fig. 1. Temperature and humidity versus electrical load in September 2014, a) temperature vs. load (correlation factor= 0.834), b) humidity versus load (correlation factor= -0.766)

Similarly, the humidity in percent versus electric loads in MW in Jordan for January 2015 is shown in Fig. 2. The figure shows also a good correlation factor with a value of 0.727 for temperature and -0.511 for humidity which means that as temperature increases the load increases and as humidity decreases the load decreases. The dependence of load on weather variables varies between winter and summer, since the tendency to consume electricity varies as much in weekend days and special holidays. Fig. 2a and 2b show temperature and humidity versus electric load in January 2015 for five days (hourly). Hence the need to construct different forecasting models for each season becomes a necessity in order to achieve maximum accuracy, which will be shown later.

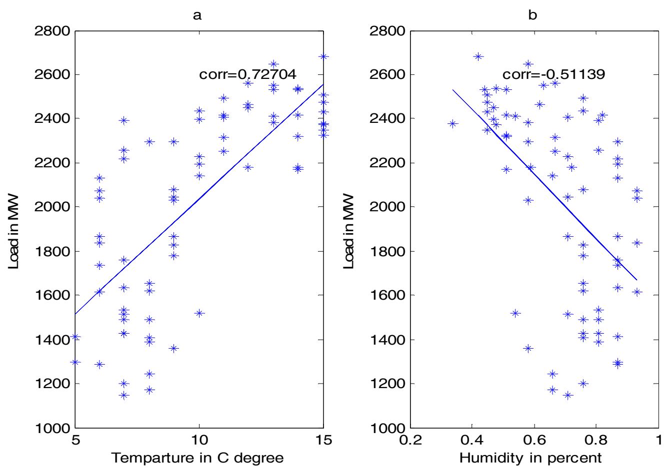

Fig. 2. Temperature and humidity versus electrical load in January 2015, a) temperature versus load (correlation factor= 0.727), b) humidity versus load (correlation factor= -0.511)

III. METHODOLOGY

The input data that is used in NARX and RBF ANN techniques has been processed in a way to obtain the minimum percentage error. In the analysis, the actual hourly loads (in MW) as well as the forecasted temperature and humidity for the next three and five days are used for STLF study. Several tests have been conducted to show the influence of the number of training days and the number of neurons variations on the normalized root mean square error values in both NARX and RBF for both summer and winter seasons. The analysis aims at showing the optimum number of training days and number of neurons that achieve the minimum percentage error. The ANN is used for solving complex problems; the artificial neurons are mainly characterized by: a) the input layer, b) the hidden layer where inputs are multiplied by weights and computed by mathematical functions to determine the activation of the neuron, c) the output layer and the output of the hidden layer (usually, the transfer function of layer neurons is linear) and d) The ANN that combines artificial neurons in order to process information. By adjusting the weights of the neural networks, the desired output from a specific input can be obtained. The process of adjusting the weights of the ANN is an iterative process which is called training. As mentioned earlier, two methods will be highlighted, NARX and radial basis neural networks. Both are different in architecture, activation functions of neurons and learning process.

A. NARX Network

In NARX network, the output is the forecasted load (in MW) as a function of the input variables that include temperature, humidity and the previous hourly load values. The NARX-ANN model is described in (3):

$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-ny), u(t), u(t-2), \ldots . u(t-nu)) \tag{3}$$

Where: *y(t)* is the next value of the dependent output signal which is regressed based on previous values of the output signal. *u(t-1)* is the previous values of an independent (exogenous) input signal. NARX model can be implemented by using a feed forward neural network to approximate the function *f* [12]. The transfer function of the hidden layer neurons is another factor that is taken into account. In our analysis, it is found that the best results can be obtained from sigmoid function. For the NARX network, several learning algorithms are used for different purposes. Gradient descent with momentum and adaptive learning rate back propagation (traingdx) is used as a learning algorithm. Fig. 3 shows a simple architecture of NARX network.

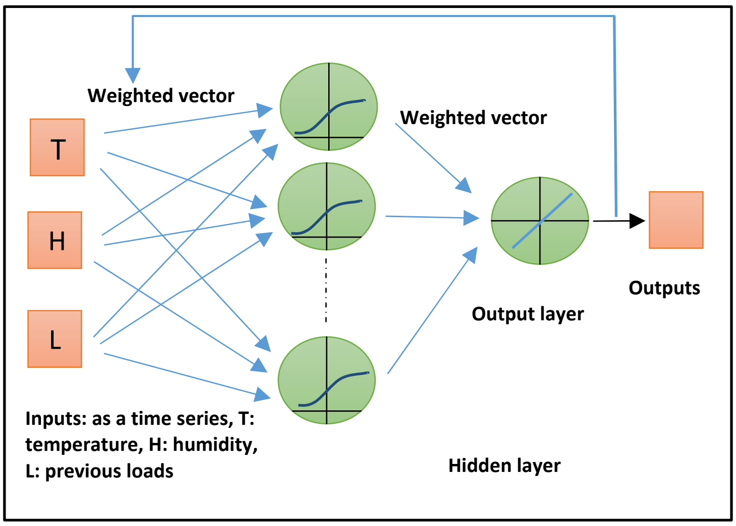

Fig. 3. Simple architecture of NARX network [11]

B. RBF Network

The output of RBF neural networks is the predicted dependent load (in MW). In this method, the handling of the input of the neuron is different from other networks, where the net input to the RBF transfer function is the vector distance between its weight vector and the input vector [7]. The distance function used is the Euclidean distance weight function multiplied by a bias. There are two types of RBF basis networks. In the first type, the number of neurons is increased iteratively until the squared error in the training process becomes lower than an error goal. However, the second type is the exact radial basis design that produces zero errors at training and produce neurons as much as input vectors. Exact RBF network is used in this paper. MATLAB is used to construct and analyze the two types of neural networks, and to plot data and results. Fig. 4 shows a simple architecture of a radial basis network.

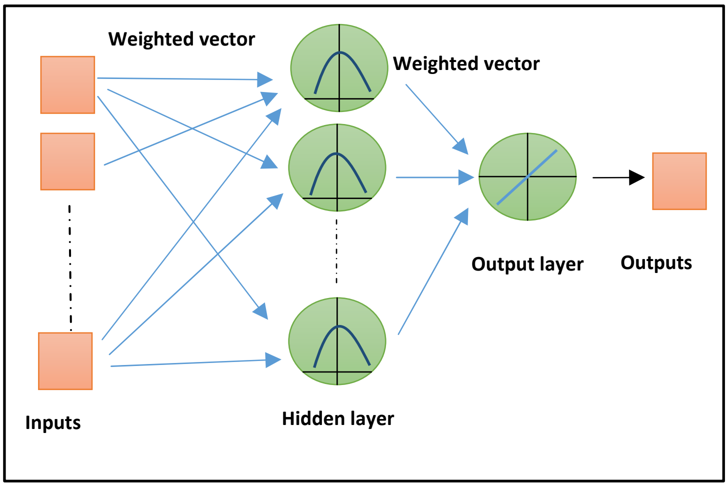

Fig. 4. Simple architecture of radial basis ANN

As mentioned earlier, two types of networks are employed. In each type, there are different parameters to be adjusted. For both techniques, the parameters are related to the architecture of the ANN and to the way the network operates. In NARX model, the number of neurons is changed then the network is trained and the error is obtained consequently. The transfer function and the logsigmoid function were adjusted to give relatively low error. In RBF model, the spreads are changed and the error is measured after the forecasted values are extracted. In order to evaluate the forecasting process for both models, four error indices were used: normalized root mean square error, mean absolute error, correlation and relative error indices:

1) Mean square error (MSE) and normalized root mean square error (NRMSE) are given by:

$$MSE = \frac{1}{n} \times \sum_{i=1}^{n} (Y_i - Y_i^{\wedge})^2 \tag{4}$$

$$NRMSE = \frac{\sqrt{MSE}}{\frac{1}{n} \times \sum_{i=1}^{n} Y_i} \tag{5}$$

2) Mean absolute error (MAE):

$$MAE = \frac{1}{n} \times \sum_{i=1}^{n} \left| Y_i - Y_i^{\wedge} \right| \tag{6}$$

3) Correlation index: the correlation between the actual and the forecasted load was determined. Compared with the two previous indices, this index gives a more reliable indication about the way the forecasted load tracks the actual load in the load shape behavior.

4) Relative error (Re) between two values:

$$Re = \frac{Y_i^{\wedge} - Y_i}{Y_i} \tag{7}$$

where,
Y_i : Actual load value in MW for hour *I*,
$Y_i^{\wedge}$: Predicted load value in MW for hour *I*,
n: number of samples (hours).

In the NARX model, high distortion was seen at the beginning of the time series (first five samples for summer and ten samples for winter) due to the time delay parameter that was optimized in the model. This affects the error indices for the future readings. The first five samples are excluded from the analysis in order to minimize the error.

IV. RESULTS AND ANALYSIS

Due to significant variations in the typical daily load curves between summer and winter seasons in Jordan, the STLF was conducted for both summer and winter seasons individually. The results obtained from NARX and RBF ANN for both seasons will be highlighted in this section.

A. Summer of 2014

The NARX and RBF networks are examined based on the data of September 2014. Hourly data for working days was used for both training and testing. Hourly loads in MW and weather data based on temperature and humidity are employed. For each day, there were 24 samples and each sample represented an hour.
Table 1 presents error indices obtained from both techniques as a function of the training days (3, 5, 7 and 9). Table 1 shows that as the training days increase from three days to five days, the accuracy of the NARX decreases significantly before it increases again. The minimum NRMSE and MAE indices were observed on five days with values of 0.0395 and 66.90 respectively. The maximum correlation was also observed on five days with a value of 92.6%. The same response was observed with RBF bus error increases significantly as training days increase. Compared with NARX, a better response was seen on five days with the values of NRMSE and MAE of 0.0354 and 59.9 respectively and correlation factor of 95.5%.

TABLE 1
NUMBER OF TRAINING DAYS AND CORRESPONDING ERROR FOR NARX AND RBF FOR SEPTEMBER 2014

Network	Error index	3 days	5 days	7 days	9 days
NARX	NRMSE	0.0892	0.0395	0.0480	0.0569
	Correlation	0.92	0.926	0.8956	0.86
	MAE	174.65	66.9092	82.9	97.4
RBF	NRMSE	0.076	0.0354	0.0759	0.0707
	Correlation	0.948	0.955	0.7304	0.773
	MAE	137.81	59.9	124.36	116.0440

Table 2 presents the NRMSE index as the function of the number of spreads and neurons for five training days in September 2014. In NARX network, the number of neurons was changed from three to 18 neutrons at fixed training days of five. The minimum error of 0.0395 was observed at three neurons. For RBF, the spreads was changed from five to 40 with minimum error of 0.0354 that was observed at 35. This agrees with the observations made by some researchers such as Hawary and Syed [2], who declared that the minimum error can be obtained when the number of neurons equals the number of input parameters.

TABLE 2
NUMBER OF NEURONS AND CORRESPONDING NORMALIZED ROOT MEAN SQUARE ERROR FOR 5 DAYS TRAINING IN SEPTEMBER 2014

RBF		NARX	
Spreads	NRMSE	Neurons	NRMSE
5	0.1141	3	0.0395
10	0.0484	6	0.0468
15	0.0440	9	0.0472
20	0.0529	12	0.04277
25	0.0521	15	0.0527
30	0.0456	18	0.0494
35	0.0354	21	0.0607
40	0.0471	24	0.0607

Fig. 5 presents the forecasted versus actual loads for 72 hours between 14 and 16 September 2014 based on NARX and RBF models. As shown in Fig. 5a, the real versus forecasted values based on NARX are in good agreement. By using RBF, the minimum load does not match the peak load, although it gives good agreement (Fig. 5b).

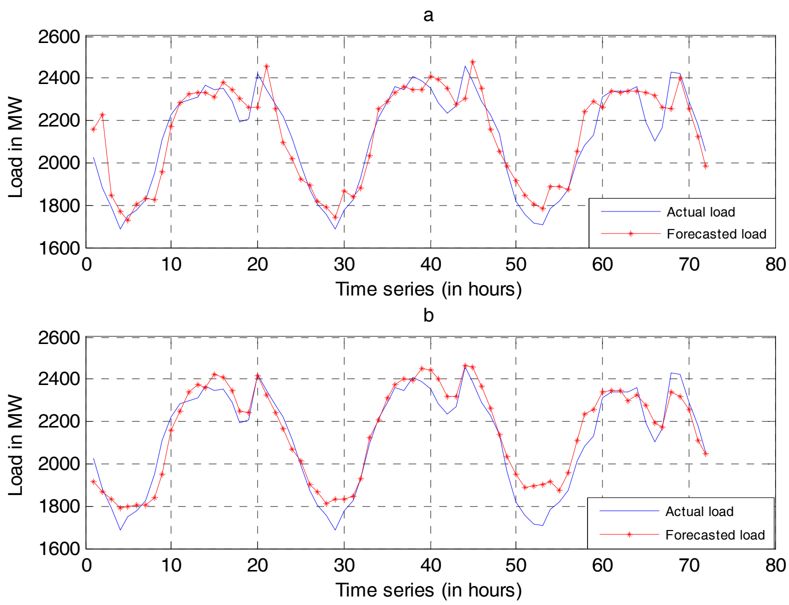

Fig. 5. Forecasted load (cross line) versus actual load (line), for 3 days (14-16 September 2014), a) using NARX, b) using RBF

The actual versus forecasted load (in MW) as a scatter plot using two techniques is shown in Fig. 6a and 6b, respectively. The results show a good correlation index with a value of 0.933 for NARX and 0.95338 for RBF. The figure also shows the periods of over or under estimation with respect to the actual load.

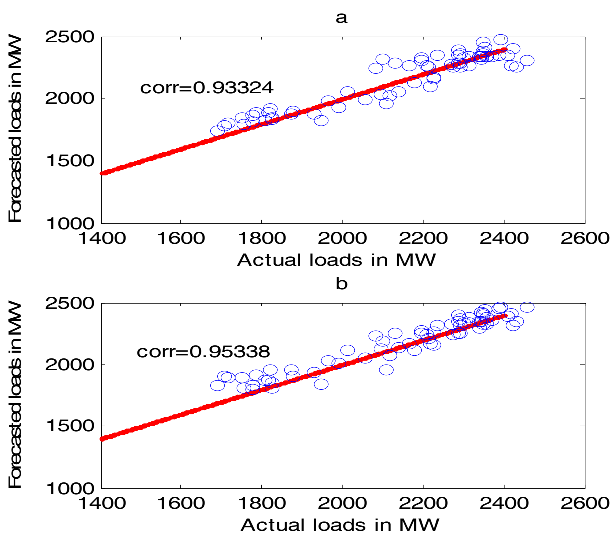

Fig. 6. Scatter plot showing the forecasted versus actual loads (MW) for September based on a) NARX, b) RBF

Finally, the actual versus forecasted daily loads based on NARX and RBF for three days between 14 and 16 September 2014 are presented in Table 3. These days represent working days. The response in holidays was not considered. The relative error was in the range between -1.2% and 1.53% for NARX and between -3.3 and 0.2% for RBF. Although the relative error of RBF was slightly lower during the first two days, it increased significantly over the NARX on the third day. It implies that NARX is more effective for long period forecasting than RBF model. The comparison between the forecasted and actual five days daily peak values obtained from NARX and RBF shows reasonable values for NRMSE, MAE and correlation indices as shown in Table 3.

TABLE 3
ACTUAL DAILY MAXIMUM VERSUS FORECASTED LOADS (IN MW) FOR 14-18 SEPTEMBER 2014 AND THE CORRESPONDING RELATIVE ERROR

	1st day	2nd day	3rd day	4th day	5th day
Actual	2420	2460	2430	2500	2450
NARX	2396.232	2440.146	2421.458	2499.246	2405.785
Re	-0.00982	-0.00807	-0.00352	-0.0003	-0.01805
RBF	2456.47	2458.973	2386.831	2356.791	2416.416
Re	0.01507	-0.00042	-0.01776	-0.05728	-0.01371
NARX vs. Actual (5 days hourly basis)			NRMSE= 0.0455, MAE= 71.2357, Correlation= 0.9207		
RBF vs. Actual (5 days hourly basis)			NRMSE= 0.0511, MAE= 73.0980, Correlation= 0.899		

B. Winter of 2015

Similarly, NARX and RBF networks are examined based on the data of February 2015. Hourly data for working days was employed for both training and testing. Hourly loads in MW and weather data based on temperature are employed. For each day, there were 24 samples each of which represents an hour. Table 4 presents the error indices obtained from both techniques as a function of the training days (3, 5, 7 and 9). Table 4 shows that as the training days increase from three to nine days, the accuracy of the NARX decreases significantly. The minimum NRMSE and MAE indices were observed on nine days with values of 0.0356 and 60.46 respectively. Maximum correlation was also observed on nine days with a value of 98.35%. The same response was observed with RBF. Error decreases significantly as training days increase. Compared with NARX, a better response was observed on nine days with the values of NRMSE and MAE of 0.0347and 59.2 respectively and correlation factor of 95.5%.

TABLE 4
NUMBER OF TRAINING DAYS AND CORRESPONDING ERROR OF NARX AND RBF IN FEBRUARY 2015

Network	Error Index	3 days	5 days	7 days	9 days
NARX	NRMSE	0.0892	0.0451	0.0452	0.0356
	MAE	0.92	73.4260	77.1780	60.4682
	Correlation	174.65	0.956	0.956	0.9835
RBF	NRMSE	0.076	0.0354	0.0346	0.0347
	MAE	137.81	59.9	61.2351	59.2272
	Correlation	0.948	0.955	0.983	0.981

Table 5 presents the NRMSE index as a function of the number of spreads and neurons for nine training days in February 2015. In NARX network, the number of neurons was changed from two to 14 neutrons at fixed training days of nine. The minimum error of 0.0356 was observed at eight neurons. For RBF, the spreads was changed from five to 40 with the minimum error of 0.0347 that was observed at 35.

TABLE 5
NUMBER OF NEURONS AND CORRESPONDING NORMALIZED ROOT MEAN SQUARE ERROR FOR 5 DAYS TRAINING IN SEPTEMBER 2014

RBF		NARX	
Spreads	NRMSE	Neurons	NRMSE
5	0.0363	2	0.0645
10	0.0359	4	0.0539
15	0.0365	6	0.0784
20	0.0347	8	0.0356
25	0.0347	10	0.0642
30	0.0347	12	0.0533
35	0.0347	14	0.0525

Fig. 7 presents the forecasted versus actual loads for three days in February 2015 (4th, 5th and 8th February) based on NARX and RBF models. As shown in Fig. 7a and 7b, although the error values obtained from NARX and RBF are close to each other, RBF has better performance in both maximum and minimum peaks except during the third day. NARX model shows high accuracy. A comparison between the results of the two models via a scatter plot between forecasted and actual loads is shown in Fig. 7a and 7b. As shown in Fig. 7a, the actual versus forecasted values based on NARX are in good agreement. By using RBF, the minimum load does not match the peak load although it gives good agreement.

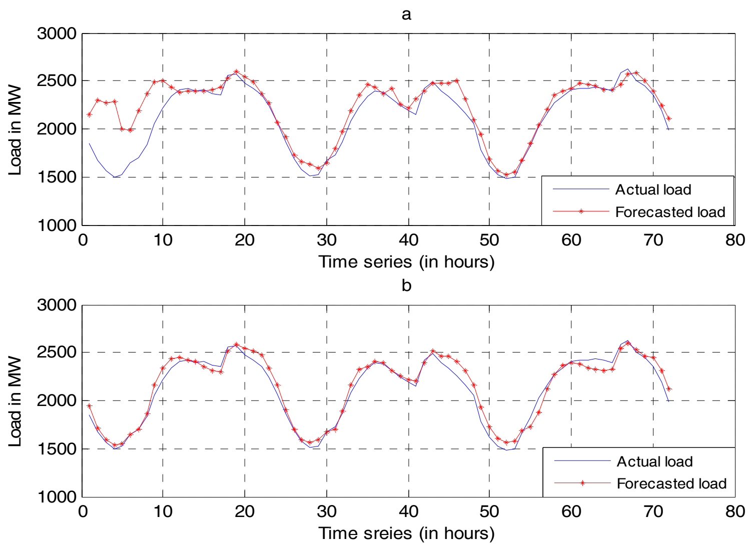

Fig. 7. Forecasted load (cross line) versus actual load (line) for 3 days (16-18 February 2015), a) using NARX, b) using RBF

The actual versus forecasted load (in MW) as scatter plot using two techniques for winter is shown in Fig. 8a and 8b respectively. The results show a good correlation index with a value of 0.983 for NARX and 0.975 for RBF. Fig. 8 also shows the periods of over or under estimation with respect to the actual load. It gives an important indication on how NARX and RBF can either overestimate or underestimate the actual load. NARX shows a more tendency to overestimate the loads (Fig. 8a), while RBF does not show any tendency from this point of view (Fig. 8b).

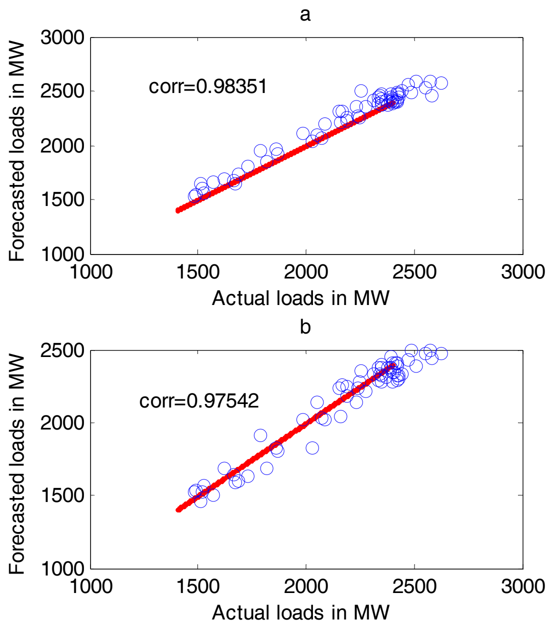

Fig. 8. Scatter plot of the forecasted versus actual loads (MW) for February 2015 based on a) NARX, b) RBF

Finally, the actual versus forecasted daily loads based on NARX and RBF for five days in February 2015 (4th, 5th, 8th, 9th and 10th February) is presented in Table 6. The relative error (Re) between the actual and forecasted was in the range between -1.59% and 0.83% for NARX and between -5.9 and 0.6 % for RBF. Although the relative error of RBF was slightly lower during the first three days, it increases significantly over the NARX in the fourth and fifth days. It implies that NARX is more reliable for long and short term forecasting than RBF model. The comparison between the actual and forecasted five days daily peak values obtained from NARX and RBF shows reasonable values for NRMSE, MAE and correlation indices.

TABLE 6
ACTUAL DAILY MAXIMUM VERSUS FORECASTED LOADS (IN MW) FOR WORKING DAYS IN FEBRUARY 2015 (4TH, 5TH, 8TH, 9TH AND 10TH FEBRUARY), AND THE CORRESPONDING RELATIVE ERROR

	1st day	2nd day	3rd day	4th day	5th day
Actual	2571.871	2483.832	2627.765	2705	2735
NARX	2568.508	2581.87	2595.973	2622.733	2646.735
Re	-0.00131	0.03947	-0.0121	-0.03041	-0.03227
RBF	2608.698	2498.965	2601.758	2594.467	2595.311
Re	0.014319	0.006092	-0.0099	-0.04086	-0.05107
NARX vs. Actual (5 days hourly basis)			NRMSE= 0.0426, MAE= 73.1901 and Correlation= 0.997		
RBF vs. Actual (5 days hourly basis)			NRMSE= 0.0375, MAE= 63.2819 and Correlation= 0.975		

V. CONCLUSIONS

The paper presents the STLF study for Jordan power grid. Two ANN approaches are implemented in the preparation of the STLF study for Jordan's case: NARX and RBF neural networks. The STLF for five days ahead was done for both summer and winter seasons. The input data implies the temperature, humidity. Four error indices are used to measure the accuracy of forecasting which implies Re, NRMSE, MAE and correlation. The comparison between hourly actual and forecasted load readings shows a reasonable normalized mean square error (NMSE) with minimum values in summer of 3.9 % for NARX and 3.5% for RBF, and in winter of 3.5% for NARX and 3.47% for RBF. The results show that the minimum error is achieved by using 5 training days for summer and 9 days for winter. The comparison between the actual and forecasted five days daily peak values obtained from NARX and RBF shows reasonable values for NRMSE, MAE and correlation indices. The comparison between the two networks shows that NARX is more reliable than RBF for forecasting the maximum daily peak for few days ahead although RBF provides lower NRMSE. The new forecasting model improves the existing forecasting models that are implemented by electrical power companies in the country. It will help reshape the load response and enhance the efficiency. It will also improve the performance of the independent system operator (ISO) and reinforce the concept of optimum operation of any power system.

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