Up to 30 Years Peak Load Forecasting of Jordanian Power Grid using Radial Basis Function Neural Networks

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Abstract— **In this paper, the Radial Basis Function Neural Networks (RBFNN) algorithm is used to forecast the electrical peak load in Jordan. The total load consumption is divided into different sectors. These sectors are; households, commercial, services, industrial, water pumping and public lighting sector. The total load forecasting is calculated by the algebraic sum of the forecasted value of the different sectors. The forecasted total energy consumption, the average temperature, and the peak temperature are used to forecast the electrical peak load. The model used to forecast the peak load utilize a small, but important, number of factors that drive the peak load demand. In order to validate the effectiveness of the model the output of the model is compared with the output of another linear regression model. The forecasted growth rate of both models and the peak load historical growth rate show that the output of the RBFNN model is more realistic.**

Keywords— **Peak Load Forecasting, Neural Networks, Radial Basis Function, Long-Term, and Electricity Consumption**

I. INTRODUCTION

Long-Term Load Forecasting (LTLF) is a crucial part in power system for planning, construction of new generating units, and electricity purchasing from generating units [1]. But with a small country like Jordan, that live almost with no natural resources, his imports from energy represent around 95% of his consumption [2] , around every ten years has a waves of refugees come in, and with the big fluctuation in energy prices, long-term load forecasting represent really a challenging problem.

Different techniques have been used to tackle the long-term load forecasting problem. These techniques can be classified into two models: (i) Linear models such as ARX, ARMA, etc.[3] . (ii) Nonlinear models such as Artificial Neural Networks (ANN) [4], Support Vector Machine (SVM) [5], and Fuzzy logic [6].

Because of the nonlinear nature of the long-term forecasting problem there was a trend in recent years to utilize the power of nonlinear models to solve this problem [7]-[11]. ANNs have great capabilities in dealing with nonlinear prediction problems. They are nonlinear in nature, can deal with huge numbers of variables, and can minimize the effect of noisy and uncertain data [7]-[11].

ANNs architectures that have been used in LTLF problem can be classified into two architectures: (i) hybrid ANN architectures and (ii) pure ANN architectures. Pure ANNs uses either the famous Backpropagation Neural Network (BPNN) model [12] or the Radial Basis Function Neural Network model [13]-[14], on the other hand, hybrid models try to combine the power of ANNs and other algorithms such as fuzzy logic, support vector machine (SVM) , Wavelet, and grey model [12],[15].

A lot of the previous models (Hybrid and pure) uses large number of factors to build a LTFL model [7]-[11]. Some of these factors are not easily to obtain in developing countries like Jordan i.e amount of $CO2$ pollution. another issue to the previous models is the large number of the hidden neurons [7]-[11].

In this paper, the RBFNN algorithm was used to forecast the electrical Peak load demand in Jordan. a small and effective RBFNN model is used to forecast the peak load demand in Jordan . The total energy consumption, the average temperature, and the peak temperature are used to forecast the electrical peak load. The model used to forecast the peak load utilize a small, but important, number of factors that drive the peak load demand.

II. RBFNN ALGORITHM

A. Structure of RBFNN

The RBFNN structure consists of three main different layers as shown in Fig. 1; one input layer (source nodes with inputs $I_1, I_2,.., I_N$), one hidden layer has K neurons, and one output layer (with outputs $y_1, y_2,.., y_m$). The input-output mapping consists of two different transformations; nonlinear transformation from the input layer to the hidden layer and linear transformation from hidden to the output layer. The connections between the input and hidden layers are called centers and the connections between the hidden and output layers are called weights [16]–[17].

The most common radial basis function used in RBFNN is given by

$$\phi_i(x) = \exp\left[-\frac{(x-c_i)^T(x-c_i)}{2\sigma_i^{\,2}}\right], \qquad i=1,2,\ldots,K \qquad (1)$$

This is a Gaussian basis function with φ_i as the output of the i^{th} hidden neoron , x is the input vector data sample ($I_1, I_2,\ldots,I_N$) (could be training, actual, or test data), c_i is centers vector of the i^{th} hidden neuron ($c_{i1},c_{i2},.., c_{iN}$), σ_i is the normalization factor, and $(x-c_i)^T(x-c_i)$ is the square of the vector $(x-c_i)$ [16]–[17]. The i^{th} output node y_i is a linear weighted summation of the outputs of the hidden layer and is given by

$$y_i = w_i^T \phi(x), \qquad i=1, 2, \ldots, m \qquad (2)$$

where w_i is the weight vector of the output node and $\Phi(x)$ is the vector of the outputs from the hidden layer (augmented with an additional bias which assumes a value of 1).

B. *Training Algorithm of RBFNN*

The block diagram shown in Fig. 2 illustrates one of the RBFNN training processes called *hybrid learning* process [18]. The *hybrid learning* process has two different stages; (i) finding suitable locations for the radial basis functions centers of the hidden neurons [17], [18] and (ii) finding the weights between the hidden and output layers. In the first stage the K-means [17], [18] clustering algorithm is used to locate the centers in the input data space regions where a significant data are present (shown as I in Fig. 2). In the second stage (shown as II in Fig. 2) the weights between the hidden and the output layers are found by linear matrix inversion algorithm based on the least-square solution, which minimizes the sum-squared error function [19].

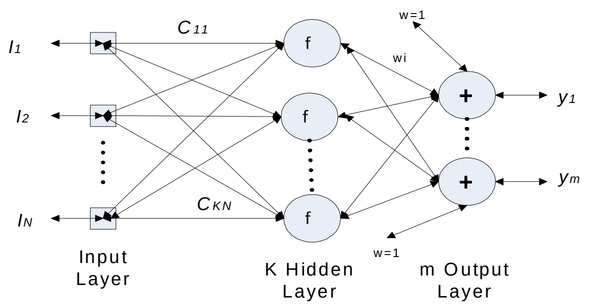

Fig. 1 Structure of RBFNN Network

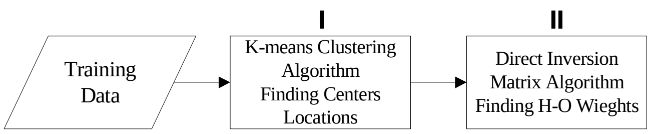

Fig. 2 Block Diagram for the RBFNN Hybrid Learning Process

The weights matrix w is given by

$$w = A^{-1}\Phi^T D \qquad (3)$$

where D is the desired output vector for l training data samples set and given by

$$D = \begin{bmatrix} d(x_1) \\ d(x_2) \\ . \\ d(x_j) \\ . \\ d(x_l) \end{bmatrix} \qquad (4)$$

where $d(x_j)$ describes the output vector corresponding to the j^{th} training data samples vector (x_j). Φ is a matrix where each element $\varphi_i(x_j)$, is a scalar value and represents the output of the i^{th} hidden neuron for the j^{th} training data samples vector (x_j). The Φ matrix for l training data samples is given by

$$\Phi = \begin{bmatrix} \phi_1(x_1) & \phi_2(x_1) & \ldots & \phi_K(x_1) \\ \phi_1(x_2) & \phi_2(x_2) & \ldots & \phi_K(x_2) \\ . & . & \ldots & . \\ . & . & & . \\ \phi_1(x_l) & \phi_2(x_l) & \ldots & \phi_K(x_l) \end{bmatrix} \qquad (5)$$

A^{-1}, the variance matrix and given by

$$A^{-1} = \left[\Phi^T \Phi\right]^{-1} \qquad (6)$$

One of the advantages of this method compare to other training algorithms is that it does not need iterations in the training phase; what it needs is the matrix inversion shown in (6), which needs negligible time to be calculated.

III. Methodology

A. *Peak Load Forecasting Model Structure*

Fig.3 shows the structure of the RBFNN peak load forecasting model. The model has three inputs: (i) the expected total energy consumption for the forecasted year. This value is obtained from the total energy forecasting model used in [20]. in that model The total energy consumption data is separated into subcategories, this separation reflects different energy pricing and consumption pattern for each sector. These sectors are; households, commercial, services, industrial, water pumping and public lighting sector [21], (ii) the expected average temperature for peak load months, and (iii) The expected peak temperature for peak load months. The novelty in this methodology is to include both the average and peak temperature for long term forecasting. It is uncommon to include the temperature for long term load forecasting but by using an accurate model forecasting model for the temperature it was possible to include these parameters.

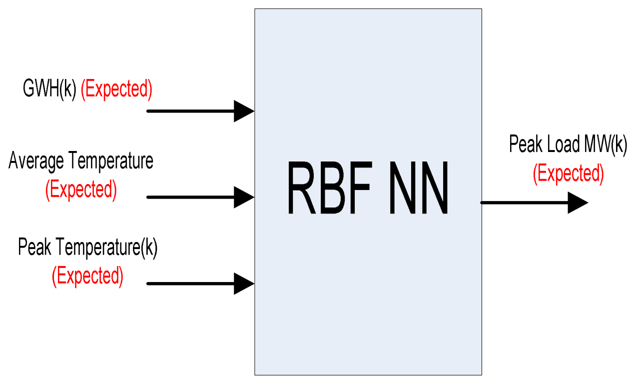

Fig. 3 structure for the RBFNN forecasting model

B. *Data Preparation*

The data for each aforementioned sectors from 1990- 2012 is used to train the RBFNN models for each sector. Then the total energy consumption data is obtained by the summation of the RBFNN models outputs[20]. In order to make the inputs of the RBFNN model homogenous, all the input data is normalized by dividing each input vector by its maximum value.

C. Model Effectiveness

the effectiveness of the model is measured by using the Mean Absolute Percentage Error (MAPE) which is calculated as :

$$MAPE = \left[\frac{1}{n}\sum_{i=1}^{n}\frac{|A_i - E_i|}{A_i}\right]$$

where

A_i : is the actual value

E_i : is the Expected (Forecasted) value

n: is the number of the sample

IV. RESULTS

The used data in the different models is provided by National Electrical Power Company (NEPCO) / Jordan. The data for the period 1990-2012 is used train the RBFNN models. The temperature data is obtained from worldbank.org. The MATLAB® software is used to build the models. The value of σ in the RBFNN models depends on the input training data. This value is obtained by running the simulation several times and selecting the value that minimizes the RBFNN network error.

The validity of the RBFNN models which are used to forecast households, commercial, services, industrial, water pumping and public lighting sector are checked first by using the data for the period 1990-2007 to train the RBFNN models and the data for the period 2008-2011 is used to validate the models effectiveness as shown in [20].

A. Total Energy Forecasting

The total energy consumption is obtained by the summation of the outputs of the forecasting models for the households, commercial, industrial, water pumping, service, and street lighting sectors. Fig. 4 shows the forecasted total energy consumption for the RBFNN model (Solid) and the linear regression model (dashed). It can be seen from the figure that the output of the RBFNN model is higher than the linear regression model till 2036 and then the output of the linear regression model will exceed the output of the RBFNN model. To understand this behavior the growth rate of the forecasted total energy consumption for both the RBFNN model and the linear regression model are plotted as shown in Fig.5. It can be seen from this figure that the growth rate for the linear regression model is almost has a flat rate and centered around seven percent. On the other hand the growth rate for the RBFNN model has approximately a hat shape, it start from around five percent, goes up to eight percent then goes down to around two percent in 2040. To validate which model forecasting is more realistic, the historical growth rate in the total energy consumption from 2001-2012 is plotted as shown in Fig.6. It is clear from comparing Fig.5 with Fig.6 that the RBFNN model is more close to the historical behavior of the system, and it is clear that the growth rate has a hat shape and goes up and down . another thing it can be seen from Fig.5 that the growth rate in the 2040 is greater than the growth rate in 2013, it is hard to imagine that at 2040 Jordan will still have that growth rate especially, with the adopting of a lot of energy efficient regulation and with the starting of applying energy star program in Jordan.

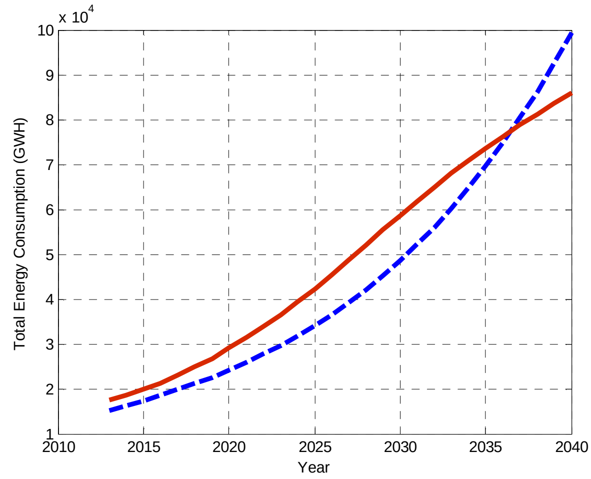

Fig. 4 Forecasted Total Energy Consumption(GWH), (Solid) RBFNN Model, (Dashed) Linear Regression Model

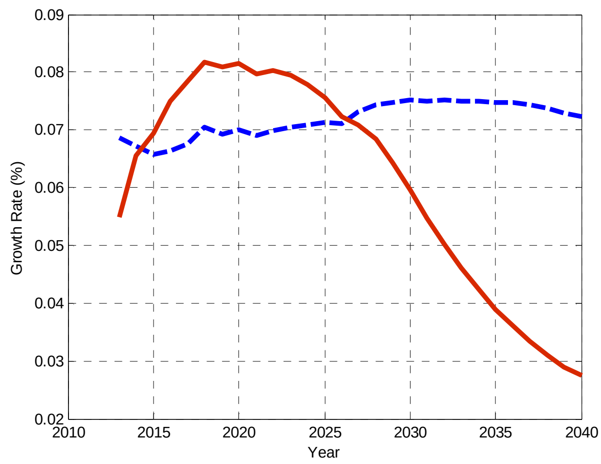

Fig. 5 Growth Rate for the Forecasted Total Energy Consumption, (Solid) RBFNN Model, (Dashed) Linear Regression Model

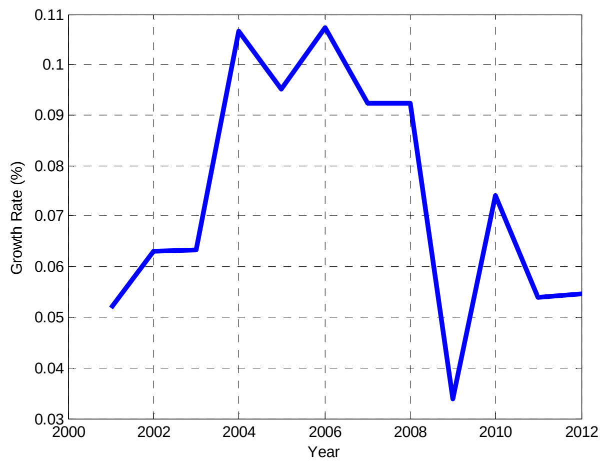

Fig. 6 Total energy Consumption Historical Growth Rate

B. Peak Load Forecasting

The data of the actual total energy consumption, average temperature, and the peak temperature for the period 2003-20011 is used train the RBFNN model to forecast the peak load. the limited data availability make it is hard to validate the model for more than one year (2012). Fig. 7 shows the actual and forecasted Peak load. The number of hidden neurons used in RBFNN model is *4* and *MAPE = 0.00006.*

Fig. 8 shows the forecasted peak load for the RBFNN model (Solid) and the linear regression model (dashed). It can be seen from the figure that the output of the RBFNN model and the output of the linear regression model are close till 2029 and then the output of the linear regression model will exceed the output of the RBFNN model and continue to increase in high rates but on the other hand the RBFNN model will tend to saturate after 2035. To understand this behavior the growth rate of the forecasted total energy consumption for both the RBFNN model and the linear regression model are plotted as shown in Fig.9. It can be seen from this figure that the growth rate for the linear regression model is keep increasing, it is start from around *four* percent and reach more than *seven* percent by 2040. On the other hand the growth rate for the RBFNN model has approximately a hat shape, it start from around *four* percent, goes up to eight percent by 2024 then goes down to around two percent in 2040. To validate which model forecasting is more realistic, the historical growth rate in the total energy consumption from 2001-2012 is plotted as shown in Fig.10. It is clear from comparing Fig.5 with Fig.6 that the RBFNN model is more close to the historical behavior of the system, and it is clear that the growth rate has a hat shape and goes up and down .

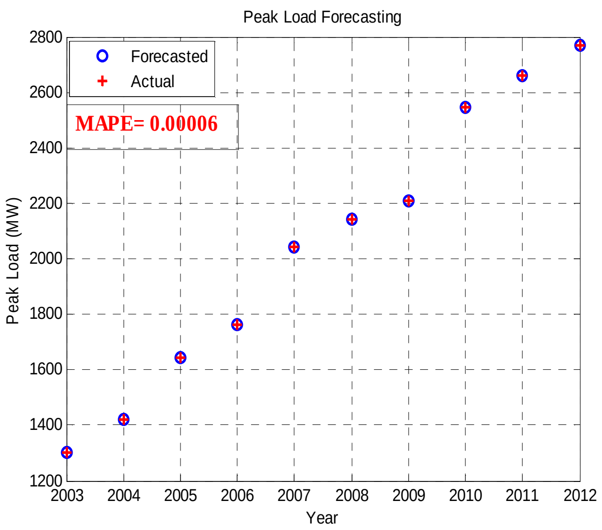

Fig. 7 peak load Forecasting, (+) Actual, (o) RBFNN Forecast with *Hn= 4.*

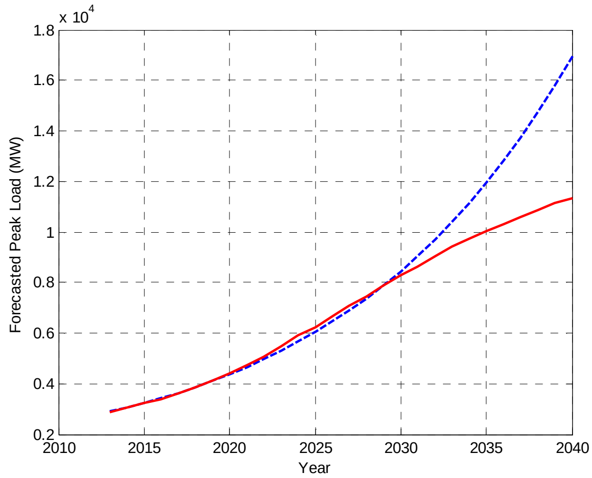

Fig. 8 Forecasted Peak Load, (Solid) RBFNN Model, (Dashed) Linear Regression Model

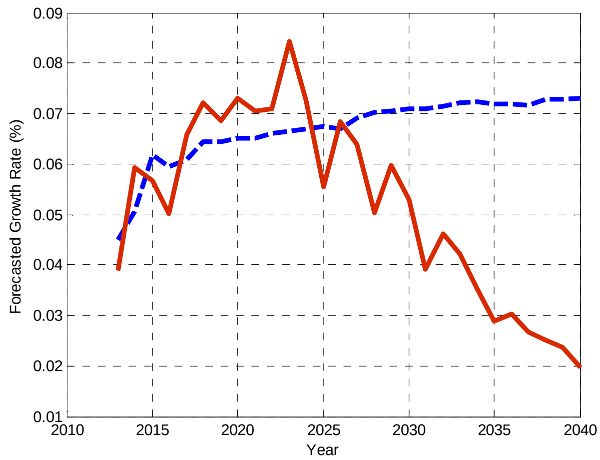

Fig. 9 Growth Rate for the Forecasted Peak Load, (Solid) RBFNN Model, (Dashed) Linear Regression Model

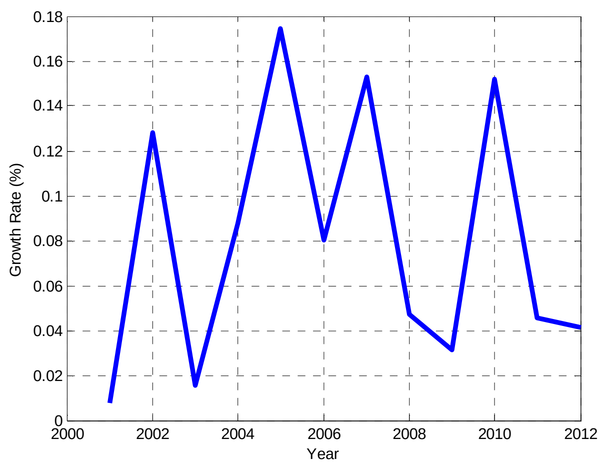

Figure 10 Peak Load Historical Growth Rate

V. CONCLUSIONS

In this paper, the RBFNN algorithm was used to forecast the electrical Peak load demand in Jordan. The total load consumption was divided into different sectors. These sectors are; households, commercial, services, industrial, water pumping and public lighting sector. a small and effective RBFNN models was used to forecast the load demand for each sector. The total load forecasting is calculated by the algebraic sum of the forecasted value of the different sectors.

The forecasted total energy consumption, the average temperature, and the peak temperature are used to forecast the electrical peak load. The model used to forecast the peak load utilize a small, but important, number of factors that drive the peak load demand. In order to validate the effectiveness of the model the output of the model is compared with the output of another linear regression model. The forecasted growth rate of both models and the peak load historical growth rate show that the output of the RBFNN model is more realistic.

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