Medium-Term Load Forecasting Using Neural Network Approach

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***Abstract*—Load forecasting is very paramount to the operation transmission and distribution electricity utilities. It enhances the reliable planning, construction and management of the power systems. This paper presents a neural network approach for mid-term load forecasting based on historical monthly load data, temperature, humidity and wind speed. The proposed approach is applied to Al-Dakhiliya franchise area of Mazoon Electricity Distribution (MZEC) Company, Oman. The results obtained by the neural networks were compared with the classical multiple linear regression models results and found more reasonable and satisfactory.**

***Index Terms*—Load forecasting, neural networks, linear regression.**

I. Introduction

POWER system unbundling and restructuring yield to corporate entities (generation, transmission, and distribution). These entities are confronted with increasing demand on reliable operation of power system networks. Accurate models for electric power load forecasting are therefore essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development.

Load forecasting can be divided into three categories: short-term forecasts which are usually from one hour to one week, medium-term forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year. Most forecasting methods use statistical techniques or artificial intelligence algorithms such as regression, time series, neural networks, fuzzy logic, and expert systems have been developed for short-, medium- and long-term forecasting.

For short-term load forecasting several factors are considered such as time factors and weather data. The medium- and long-term forecasts take into account historical load, weather data, the number of customers in different categories, the economic and demographic data and their forecast, and other factors.

Weather conditions influence the load. In fact, forecasted weather parameters are the most important factors in short- and mid-term load forecasts. Various weather variables could be considered for load forecasting. Temperature, humidity and wind speed are the most commonly used load predictors.

This paper presents a mid-term load forecasting model based on neural network approach. Three neural networks are developed to forecast the monthly peak load for months ahead for the three franchise regions of MZEC Distribution Company using historical monthly peak loads and weather data for 2006-2010. The inputs used for the neural networks are the month index, temperature, relative humidity, and wind speed.

II. Overview of MZEC Distribution System

Mazoon Electricity Company (MZEC) is primarily undertaking regulated distribution and supply of electricity in three franchise regions, namely Al-Dakhiliya, Al-Sharqiya and South AL Batinah regions as shown in Fig. 1. The company took over the assets and liabilities as on 1st May 2006.

Fig. 1. Mazoon Authorized Franchise Regions

Due to weather characteristics in Oman, demand for electricity varies between the summer period (May-August) and the winter period. The demand increases to its full extent during summer and decreases significantly during non summer. Figure 2 shows the monthly demand profile of the Mazoon distribution system over the years 2007-2010. The significant increase in electricity demand and therefore in energy consumed during summer period is influenced by the

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need for operating air conditioners to overcome the high degree of temperatures which reaches 45 ºC.

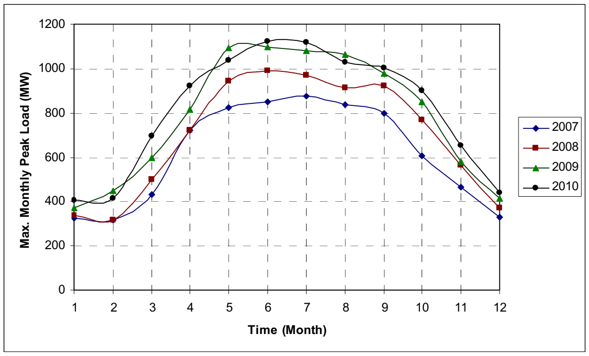

Fig. 2. Maximum monthly peak load curve of Mazoon distribution system

III. Load Forecasting Models

Linear regression and neural network based load forecasting models have been developed in this work to forecast the monthly peak load for the regions of MZEC Company. These models take into consideration the variation of the monthly peak loads with the variation of the weather data conditions such as maximum temperature, humidity and wind speed over the year. In this summary the results of Al-Dakhiliya region will be presented.

The variation of the monthly peak loads and the variations of the weather conditions are displayed in Figs. 3-6. It can bee seen that the variation of the peak load and temperature over the year follows the same trend indicating that both are highly linearly related. On the other hand, Figs. 5 and 6 indicate that the variation of both of the humidity and wind speed is not smoothly related to the variation of the peak loads.

A. Linear regression Model

In this paper a linear regression in the form of (1) is proposed.

$$P_L = a_o + a_1 X_1 + a_2 X_2 + a_3 X_3 + a_3 X_4$$
$$P_L = a_o + a_1 Month + a_2 Temp + a_3 Hum + a_4 WS \quad (1)$$

where

X_1, X_2, and X_3 represent the month index (1,2,…,12), temperature, humidity and wind speed, respectively.

P_L is the forecasted peak load month a head.

a_o, a_1, a_2, a_3 and a_4 are the model's unknown coefficients that can be found using the least-square error (LSE) technique.

The historical data have been divided into two groups. The training data of years 2006-2009 have been used to obtain the coefficients, whereas the testing data of 2010 have been used to examine the forecasting performance of the developed models. Using the LSE technique values of the coefficients are found to be:

$\boldsymbol{a_o}$ = -119.3, $\boldsymbol{a_1}$ = 2.0 , $\boldsymbol{a_2}$ = 10.0 , $\boldsymbol{a_3}$ = -1. , $\boldsymbol{a_4}$ = -0.0

Examining the coefficients of the linear regression model, one can see that peak load has minor linear dependence on both of the humidity and wind speed. It is mainly the month index and the temperature variables that linearly influence the forecasted monthly peak loads.

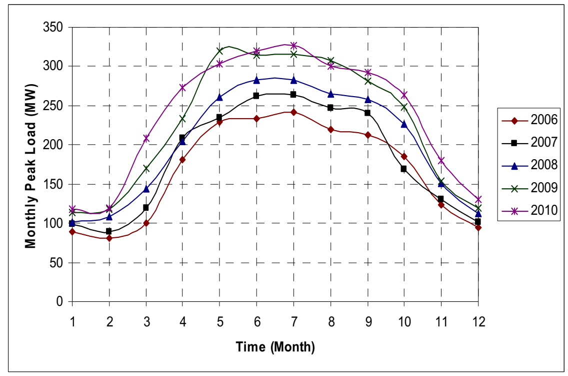

Fig. 3. Monthly variations of peak loads of Al- Dakhiliya

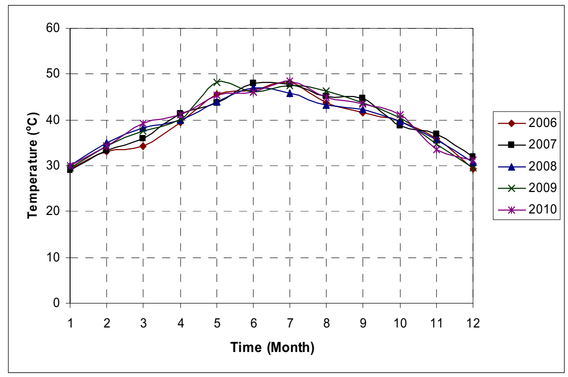

Fig. 4. Monthly variations of temperature of Al- Dakhiliya

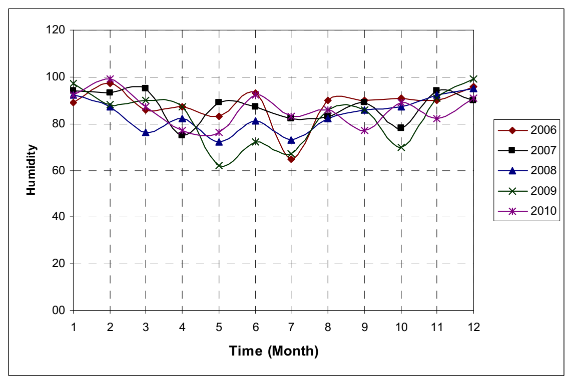

Fig. 5. Monthly variations of relative humidity of Al- Dakhiliya

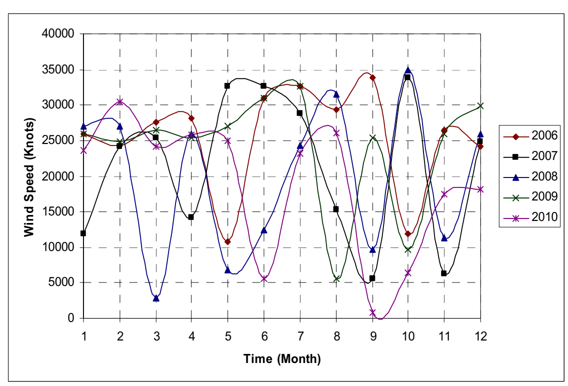

Fig. 6. Monthly variations of wind speed of Al- Dakhiliya

Figure 7 shows the actual and estimated monthly peak loads over the four years 2006-2009. The estimated loads were obtained using the developed linear regression model. Likewise, Fig. 8 shows the actual and estimated (forecasted) monthly peak loads for the year 2010.

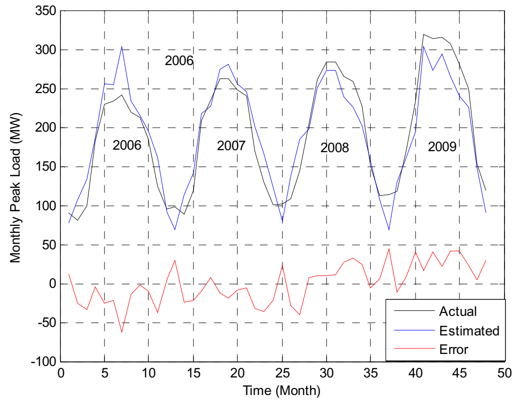

Fig. 7. Comparison of Al- Dakhiliya actual and estimated monthly peak loads for 2006-2009.

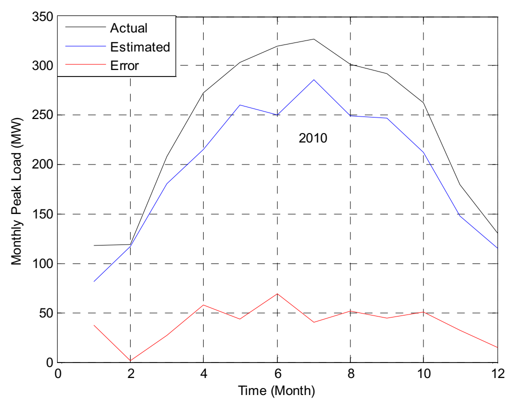

Fig. 8. Comparison of Al-Dhakiliya actual and estimated monthly peak loads for years 2010.

The training and testing performance of the linear regression model has been evaluated in terms of the mean square error (MSE) and mean absolute error (MAE) where,

$$MSE = \frac{1}{N}\sum_{p=1}^{N}\left(Actual_p - Estimated_p\right)^2 \qquad (2)$$

$$MAE = \frac{1}{N}\sum_{p=1}^{N}\left|Actual_p - Estimated_p\right| \qquad (3)$$

TABLE I
TRAINING AND TESTING PERFORMANCE OF THE LINEAR REGRESSION MODEL

Phase	MSE	MAE
Training	144.3	12
Testing	1372	37

Examining Figs. 7 and 8, and Table I, one can see that the linear regression produces large error. Therefore, an alternative approach which considers the nonlinear relation between the peak load and the weather data should be investigated.

B. Neural Network Model

In order to improve the mid-term load forecasting of monthly peak load considering the effect of the weather conditions, a neural network (NN) approach using backpropagation (BP) training algorithm has been followed to develop a non-linear forecasting models.

A BPNN model has been created. Different NN architectures were examined with different number of hidden layers and different number of hidden neurons. Also, different BP training algorithms and different activation functions have been tested. After several trial and error study cases, it was found that a NN architecture of two hidden layers, four inputs and one output is the most suitable architecture. Moreover, the "*logsigmoid*" activation function has been used in both of the hidden layers and the output layer as shown in Fig. 9.

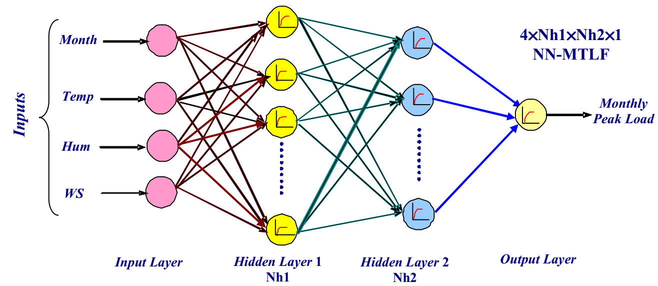

Fig. 9. Architecture of proposed neural network mid-term load forecaster

Several MATLAB computer simulations were run for Al-Dakhiliya region to find the proper number of hidden neurons in the two hidden layers. Since, there is no firm rule that tells how to choose the number of hidden neurons, a trial and error approach has been followed and satisfactory goal performance is achieved. In this study, the goal performance was set to 0.001.

To train the proposed NN the available data has been divided into two sets. One set of data is called training data and includes the data over years 2006-2009 (4 years). The second set of data is called testing data and includes the data of year 2010.

After several computer simulations the suitable number of hidden neurons (Nh1 and Nh2) and the training and testing performance indices (MSE) and (MAE) along with the number of training epochs are found and given in Table II.

TABLE II
TRAINING AND TESTING PERFORMANCE MEASURES OF NN-MODEL

Training Performance		Testing Performance		# Hidden Layer Neurons		# Training Epochs
MSE	MAE	MSE	MAE	Nh1	Nh2	
56.94	5.16	204.74	11.96	60	15	2105

The training performance for the proposed NN in terms of error convergence performance and comparison between the actual and NN estimated data are displayed in Figs. 10 and 11. Examining the results one can see that the training is performed satisfactorily with high degree of accuracy and both actual and estimated monthly peak load data almost match each other. Also the training performance is given in Table II in terms of MSE and MAE.

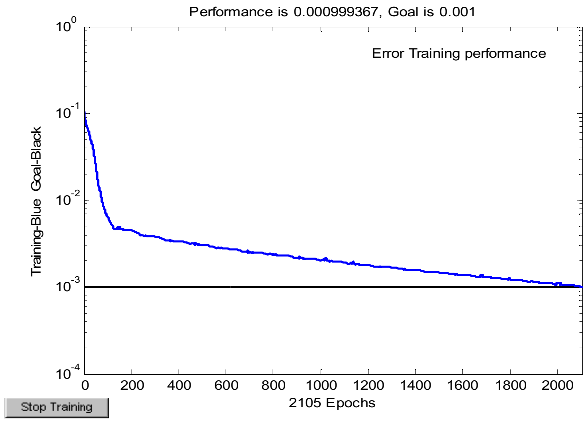

Fig. 10. Training Error Convergence of Al-Dhakhiliya NN

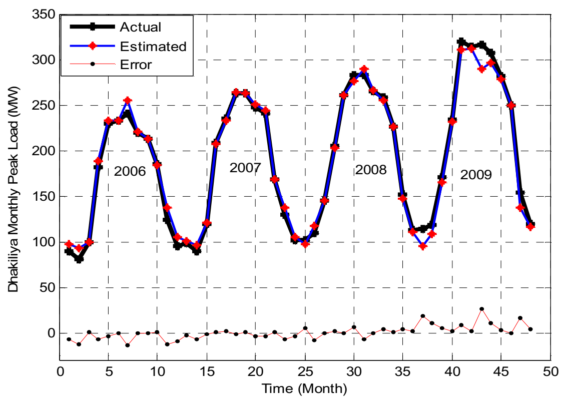

Fig. 11. Comparison between actual and estimate monthly peak load of Al-Dakhiliya NN-MTLF-training phase, years 2006-2009Template

Like wise, the generalization capability of the proposed NN is tested by forecasting the monthly peak loads of year 2010. These results of load forecasting in the testing phase are illustrated in Figs. 12.

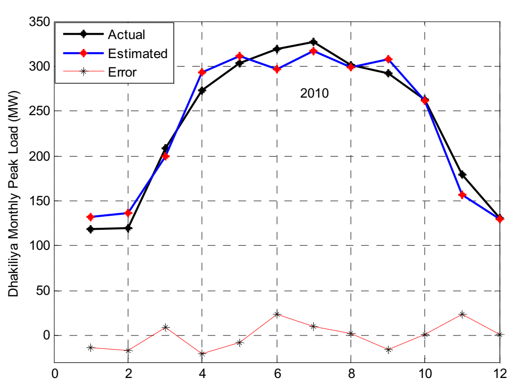

Fig. 12. Comparison between actual and estimate monthly peak load of Al-Dhakiliya NN-MTLF-forecasting phase, years 2010.

The forecasting performance was also assessed in terms of MSE and MAE as indicated in Table II. The performance indices and the simulation results show that the nonlinear neural network models outperform the linear regression model. Figure 12 shows that the forecasting accuracy is relatively satisfactory. However, the accuracy can be much improved if more training and testing data were available.

IV. Conclusions

Two techniques, based on linear regression and neural-network, for mid-term load forecasting of Al-Dakhiliya distribution system have been developed in this paper. The developed models comprise the historical monthly load data, temperature, humidity and wind speed. The simulation results shows that the neural network nonlinear based model outperforms the classical multiple linear regression model and found more reasonable and satisfactory.

V. Acknowledgment

The authors gratefully acknowledge the support of Sultan Qaboos University, Muscat, Oman.

VI. References

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VII. Biographies

Eyad Feilat (M'1991, SM'2004) was born in Jordan, in 1964. He obtained his B.Sc. in Electrical Engineering in 1987 from the University of Jordan, his M.Sc. degree in 1989 from the Jordan University of Science and Technology, and his Ph.D. from Mississippi State University in 2000.

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Mounir Bouzguenda received his B.S. degree in Electrical Engineering the Pennsylvania State University, USA, in 1985. He also received his M.S. and Ph.D. degrees in Electrical Engineering from Virginia Polytechnic Institute and State University, USA in 1988 and 1992, respectively.
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