# Modeling and Forecasting Short-Term Electricity Demand for Libyan Electric Network

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*Abstract*—**Electrical load forecasting is a method of guessing the future of the electricity demand. Load forecast is an essential factor for power system planners and demand controllers. This is to ensure that would be an adequate amount of the electricity meeting the increasing demands. Therefore, an accurate load forecasting model can effectively lead to reduction of power system cost, better budget planning, and maintenance scheduling. The future load on a power system is predicted by extrapolating a predetermined relationship between the load and its influential variables. Determination of this relationship involves modeling and estimation the coefficient of the model through the use of an efficient parameter estimation technique. This paper presents a short term forecasting model for Libyan electric network using multi parameter regression method. The proposed method shows a result with small deviation between the actual and expected load, which means Multi parameter regression emerged as a suitable model for forecasting electricity demand in Libya.**

*Index Terms:* **short term load forecasting, Multi parameter regression, Power system.**

## I.   INTRODUCTION

Forecast is a prediction of future events. Today the most used thing in the world is energy. Energy forecasting categorized as short term, medium-term and long term. Short-term load forecasting predicts events only few time periods such as hours, days, and weeks into future. Medium term forecast predicts event from one month to one year into future and long term forecast predicts through many years. Nowadays, with the recent move towards deregulation in the electric industry, short term load forecasting (STLF) becomes important and constituent to market. Up to date many method have been used for load forecasting. Generally they can be classified into two categories statistical and intelligence techniques. Statistical methods include regression model, time series, and quadratic discriminant.  On other hand intelligence techniques include neural network, support vector machine, genetic algorithm, and decision tree induction [1, 2].

## II.   TYPES OF LOAD FORECASTING

According to the forecasting period, load forecasting mainly classified into three categories, which are short term load forecasting, medium term load forecasting, and long term forecasting. Load forecasting is an integral part of electric power system operations. Long lead time forecasts of up to 20 years ahead are needed for construction of new generating capacity as well as the determination of prices and regulatory policy. Medium term forecast predicts event from month to one year ahead. It is necessary for power scheduling, power sharing arrangements and setting of electricity cost so demand can be met with fixed capacity. Short term forecasts predicts few hours to a few weeks ahead. STLF is essential for the economic secure operation of the electric utility system. Generating units, start-up or shut-down, unit commitment, on-the scheduling is considered essential function that affected by the accuracy of the STLF [2, 3]. Another area of application involves power system security studies and load flow studies, including contingency planning load shedding and load management strategies [4].

## III.   TECHNIQUES FOR SHORT-TERM LOAD FORECACTING

A large variety of statistical and intelligence techniques have been developed for STLF. The statistical techniques are such as linear and nonlinear regression analysis [5, 6], and time series models [7, 8]. Otherwise, the intelligence techniques can be divided into three subgroups depending on the artificial intelligence paradigm that they represent, namely Artificial Neural Networks (ANN), including the multilayer perceptron (MLP), radial basis function (RBF) and Support Vector Machine (SVM) [9- 13], fuzzy systems [14, 15, 16] and hybrid models [17]. However, for Libyan power system, a few attempts can be found in the literature investigating techniques to increase the accuracy and efficiency of load forecasting models. In [18], a multiple linear regression method is presented forecasting the electricity demand for short term (up to one month) and long term (up to 2020). Furthermore, in [19] an End-use method is presented as a way to predict the electricity demand up to year 2030. In addition, the Time Series Stochastic Method was used by [20] for forecasting the electricity demand from 2011 to 2022.

In this paper, an attempt to utilize a multi parameter regression technique to predict the daily peak load for a week ahead and to increase the forecasting accuracy of Libyan power system. Algorithms implementing these forecasting techniques have been programmed using MATLAB.

## IV. FACTORS AFFECTING LOAD DEMAND

Several numbers of factors affect the load demand considerably. The impacts of all these factors which affect the load need to be studied in order to develop an accurate load forecasting model. Many economic factors such as the type of customers such as residential, agricultural, commercial and industrial, demographic conditions, population, per capita income, growth, national economic growth (GDP), and social activities etc. can cause a considerable change in the load pattern. These economic factors mainly affect the long and medium-term load forecasting. On the other hand, STLF is greatly affected by weather conditions such as temperature (dry bulb and wet bulb temperature), humidity, cloud coverage etc. The most important weather factor is the temperature. The changes considerably affect the load requirement for heating in winter and air conditioning in summer. STLF also affected by other factors such as humidity especially in hot and humid areas, precipitation, thunderstorms, wind speed and light intensity of the day. In addition, time and seasonal factors play an important role in forming load pattern. Moreover, load pattern might be varied by random disturbances that occur in the power system. The random disturbances include sudden shutdown or start of industries, wide spread strikes, marriages, special functions etc. [21].

## V. MULTI PARAMETER REGRESSION

Multi parameter regression (MPR) method is one of the most widely used statistical techniques for short-term and medium-term load forecasting. It measures the impact of multi-independent variable over one dependent variable. In STLF, the MPR is generally used to model the relationship between load consumption and factors affecting load consumption such as weather that include temperature, humidity and wind speed [22]. The original MPR model, which includes the number of n independent variables, can be expressed by the equation [24, 20]:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + U_i \quad (1)$$
$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ji} + U_i \quad (2)$$

Where $y_i$ is the dependent variable, $\beta_0$, $\beta_2$, ... ..., $\beta_k$ are the regression coefficients, $x_{1i}$, $x_{2i}$, $x_{3i}$, ... ..., $x_{ki}$ are the independent variables, and $U_i$ is the random error that reflecting the difference between the observed and fitted linear relationship.

Equation (2) is the general form of the single following equations:

$$y_1 = \beta_0 + \beta_1 x_{11} + \beta_2 x_{21} + \cdots + \beta_k x_{k1} + U_1$$
$$y_2 = \beta_0 + \beta_1 x_{12} + \beta_2 x_{22} + \cdots + \beta_k x_{k2} + U_2$$
$$y_3 = \beta_0 + \beta_1 x_{13} + \beta_2 x_{23} + \cdots + \beta_k x_{k3} + U_3$$
$$\vdots \qquad \vdots \qquad \vdots \qquad \vdots \qquad (3)$$
$$y_n = \beta_0 + \beta_1 x_{1n} + \beta_2 x_{2n} + \cdots + \beta_k x_{kn} + U_n$$

Equations shown in (3) can be represented in matrix form as following:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \cdot \\ \cdot \\ \cdot \\ y_N \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & x_{21} & \cdot & x_{K1} \\ 1 & x_{12} & x_{22} & \cdot & x_{K2} \\ 1 & x_{13} & x_{23} & \cdot & x_{K3} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 1 & x_{1N} & x_{2N} & \cdot & x_{KN} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \cdot \\ \cdot \\ \cdot \\ \beta_K \end{bmatrix} + \begin{bmatrix} U_1 \\ U_2 \\ U_3 \\ \cdot \\ \cdot \\ \cdot \\ U_N \end{bmatrix} \quad (4)$$

$$\bar{Y} = \bar{X}\beta + \bar{U} \quad (5)$$

Where Y is a column vector of order $(N*1)$, X is a matrix consists of the independent variables, $\beta$ is a column vector of order $[1*(1+P)]$ consists of the unknown regression coefficients, and U is a column vector of order a $(N*1)$ consists of the random variable values.

Considering the relationship of predictive variables are:

$$Y_i' = b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots + b_p X_{pi} + e_i \quad (6)$$

Where $Y_i'$ is the expected value for the dependent variables, $b_0, b_1, b_2, \ldots, b_p$ are the value of $\beta_0, \beta_1, \beta_2, \ldots, \beta_p$ respectively, and $e_i$ is the difference between the real value and the expected value.

Least squares method can be used to estimate the MPR model coefficients as following [22]:

$$Y = Xb + e \quad (7)$$
$$e = Y - Xb \quad (8)$$
$$e^T e = (Y - Xb)^T (Y - Xb) \quad (9)$$
$$e^T e = Y^T Y - 2b^T X^T Y + b^T X^T Xb \quad (10)$$

By partial differentiation of Equation (10) and equating by zero, gives:

$$\frac{\partial}{\partial b}(e^T e) = -2X^T Y + 2X^T Xb = 0 \quad (11)$$
$$(X^T X)b = X^T Y \quad (12)$$

Multiplying equation (12) in $(X^T X)^{-1}$

$$(X^T X)^{-1}(X^T X)b = (X^T X)^{-1} X^T Y \quad (13)$$
$$b = (X^T X)^{-1} X^T Y \quad (14)$$

Where b is the regression coefficient to be found.

# VI. APPLICATION OF STLF MODEL ON LIBYAN ELECTRIC NETWORK

Considering the peak load of the Libyan electric network and weather data, the MPR short forecasting model will be applied, but first the model should be verified using old available data. A data for daily peak load and weather are collected for year 2016. The methodology is to determine the regression model for the first week of August 2016, which represents the relation between daily peak load ( $y_i$) with respect to temperature (T), humidity (H), and wind speed (W). the regression model that found from historical date of first week of August 2016 can be used for the second week of August 2016 considering the expected weather data (T, H, and W) for such week to estimate the daily peak load. Assuming that the daily peak load ($y_i$) and the weather data (T, H, and W) for the first week of August 2016 are given in table 1.

Table 1. Data for the First Week of August 2016 [23, 24]

| Day | Peak load (MW) | T (C)$^0$ | H (%) | W (Mph) |
|---|---|---|---|---|
| 1 | 6363 | 31 | 74 | 9 |
| 2 | 6550 | 31 | 78 | 12 |
| 3 | 6263 | 29 | 78 | 12 |
| 4 | 6216 | 29 | 69 | 9 |
| 5 | 6060 | 30 | 70 | 13 |
| 6 | 6435 | 30 | 74 | 13 |
| 7 | 6100 | 29 | 65 | 12 |
| 8 | 6100 | 29 | 65 | 10 |

According to the equation (1), the regression model that includes three independent variables and one dependent variable can be written as following:

$$y_i = \beta_0 + \beta_1 T + \beta_2 H + \beta_3 W \qquad (15)$$

The matrix form equations can be written as:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \\ y_7 \\ y_8 \end{bmatrix} = \begin{bmatrix} 1 & T_1 & H_1 & W_1 \\ 1 & T_2 & H_2 & W_2 \\ 1 & T_3 & H_3 & W_3 \\ 1 & T_4 & H_4 & W_4 \\ 1 & T_5 & H_5 & W_5 \\ 1 & T_6 & H_6 & W_6 \\ 1 & T_7 & H_7 & W_7 \\ 1 & T_8 & H_8 & W_8 \end{bmatrix} * \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} \qquad (16)$$

By substituting the values of $y_i$, T, H, and W in the equation (16) from data in table (1), it can be rewritten as following:

$$\begin{bmatrix} 6363 \\ 6550 \\ 6263 \\ 6216 \\ 6060 \\ 6435 \\ 6100 \\ 6100 \end{bmatrix} = \begin{bmatrix} 1 & 31 & 47 & 9 \\ 1 & 31 & 78 & 12 \\ 1 & 29 & 78 & 12 \\ 1 & 29 & 69 & 9 \\ 1 & 30 & 70 & 13 \\ 1 & 30 & 74 & 13 \\ 1 & 29 & 65 & 12 \\ 1 & 29 & 65 & 10 \end{bmatrix} * \begin{bmatrix} \beta_0 \\ \beta_2 \\ \beta_3 \\ \beta_0 \end{bmatrix} \qquad (17)$$

By using **MATLAB**, $\beta_0$, $\beta_1$, $\beta_2$, $\beta_3$ are found as:

$$\beta_0 = 2842.3, \quad \beta_1 = 21.1, \quad \beta_2 = 68.4, \quad \beta_3 = -11.4$$

The regression model for the first week of August 2016 is found to be:

$$Y_F = 2842.3 + 21.1 H_F + 68.4 T_F - 11.4 W_F \qquad (18)$$

As the forecasted weather data can be obtained, the forecasted peak load for the second week of the same month can be estimated by substituting the forecasted weather data, that is given in table II, in the regression model in (18).

Table 2. Forecasted Data for the Second Week of August 2016 [24]

| Day | $T_F$ ( $C^0$) | $H_F$ (%) | $W_F$ (mph) |
|---|---|---|---|
| 1 | 29 | 65 | 10 |
| 2 | 31 | 78 | 9 |
| 3 | 32 | 70 | 15 |
| 4 | 29 | 69 | 12 |
| 5 | 29 | 69 | 14 |
| 6 | 29 | 74 | 13 |
| 7 | 30 | 69 | 17 |
| 8 | 29 | 69 | 16 |

To validate the proposed method, the Mean Absolute Percentage Error (MAPE) can be calculated as following [24]:

$$\text{MAPE} = \frac{100}{n} \Sigma \left| \frac{\text{Actual load-Expected load}}{\text{Actual load}} \right| \qquad (19)$$

Where n is the forecasted period.

The procedure that was done for the second week of August of 2016 can be repeated consequently for the next weeks of the same month, using second week model for the third week and the third week model for the fourth week and so on. The proposed method is verified for the one month of each season. The month of, August 2016, November 2016, January 2016, and April 2016 are chosen to represent the summer, autumn, winter, and spring respectively. As the short term load forecasting predicts the load a one week ahead, each month is divided to four weeks.

## VII. SIMULATION RESULTS AND DISCUSSION

The proposed technique was tested using four months of real data. The test data included a daily peak load and weather data for four months in year 2016. Table 1 shows the data for the first week of August 2016 that used for explaining the multi parameter regression procedure. The test data was selected in such a way as to include one month of each season and weather characteristics that affect load demand. Forecasting was performed for each week of each month separately. Figure 1 shows the actual and expected peak load for the four weeks of the month of August 2016. The forecasting results of figure 1 reveal that the deviation between the actual and forested load is within the acceptable rang, where the MAPE of four weeks were 2.07 %, 2.12%, and 4.88% respectively. Small deviation is good indication that MPR good method for STLF. In addition, Small error confirms that the weather factors play an important role in the electricity demand. However, Figure 2, 3, and 4 show results of the Month of January, April, and November of the year 2016 respectively.
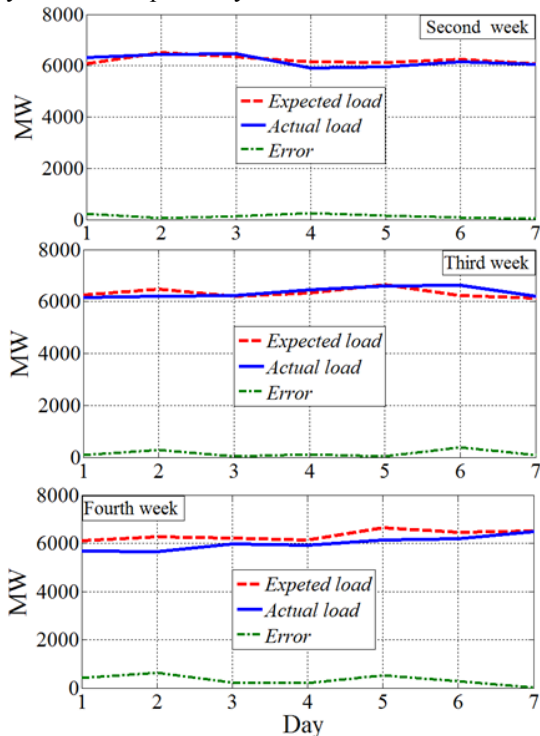


Figure 1. Actual and Expected Peak load for 3 Weeks of the Month of August 2016.
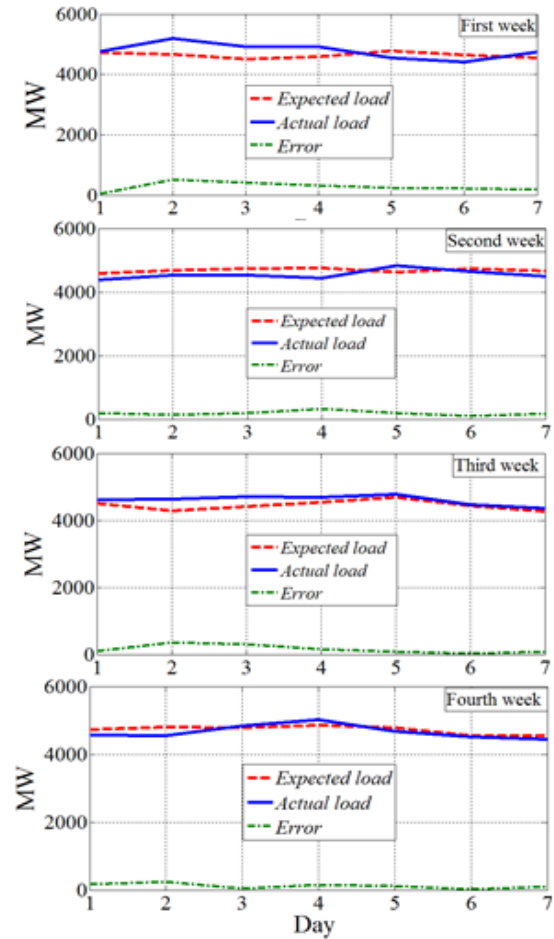


Figure 2. Actual and Expected Peak Load for 4 Weeks of the Month of January 2016
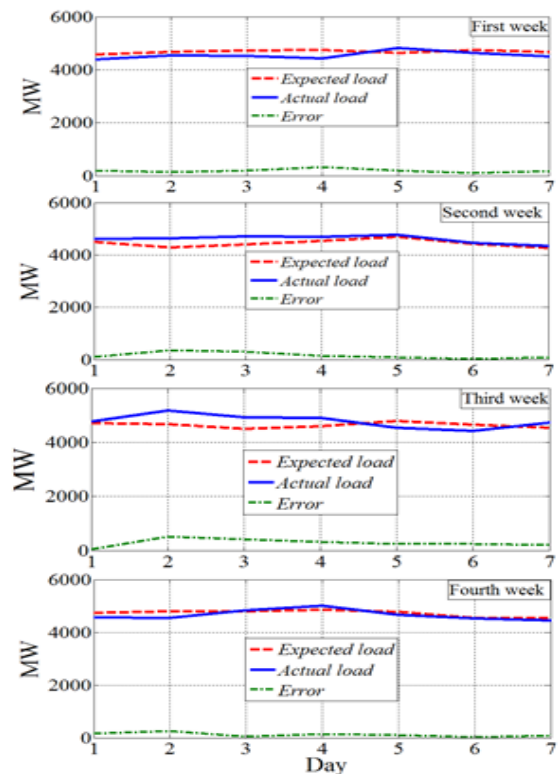


Figure 3. Actual and Expected Peak Load for 4 Weeks of the Month of April 2016
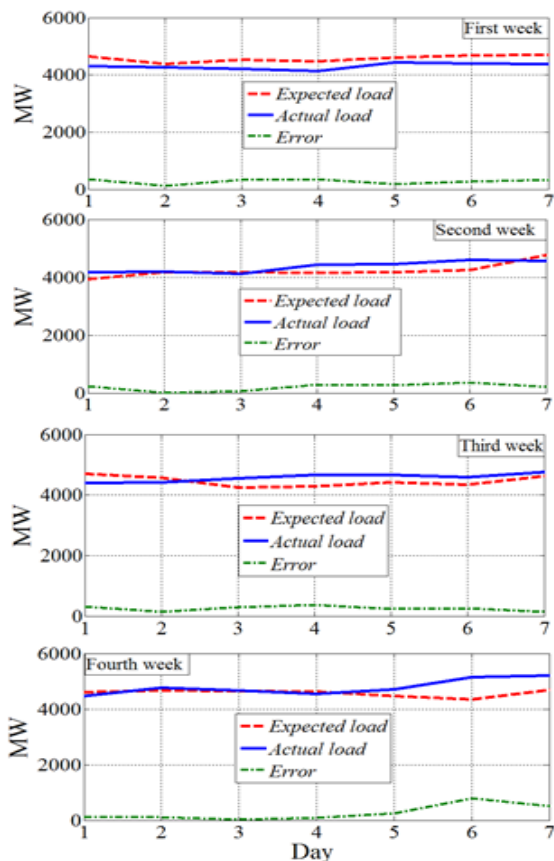
Figure 4.    Actual and Expected Peak Load for 4 Weeks of the Month of November 2016

## VIII.    CONCLUSIONS

Load forecasts is divided into three categories: short-term forecasts which are usually from one hour to one week, medium forecasts which are usually from a month to a year, and long-term forecasts which are longer than a year. STLF is a very useful tool for security analysis, start-up or shut-down, unit commitment, and economic dispatch. Therefore, the accurate forecasting of the load is an essential element in power system. In this paper, an attempt to forecast the daily peak demand of electricity for a week ahead by using an appropriate multi parameter regression model. The load forecasting results are shown that the weather factor is an important factor effecting electric system loading. Moreover, results of the MAPE are indicated that the proposed method is a good way for improving the load forecasting accuracy.

## ACKNOWLEDGMENT

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