Long Term Peak Load Forecasting for the Libyan Network

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ABSTRACT

Long term load demand forecasting is a necessary process in electric power system operation and development. It contains the accurate prediction of both magnitudes and geographical locations of electric load over the different periods of the planning horizon. Several economic implications of power utility such as economic scheduling of generating capacity, scheduling of fuel purchases, security analysis, planning of power development, maintenance scheduling and dispatching of generation units are mainly worked based on accurate load forecasting. In this paper, the peak load for seven years ahead is performed for the Libyan electric network with the simple regression method. MATLAB programming has been used for computational work. The results attained are validated with the real data obtained from the National Control Center of the General Electricity Company of Libya (GECOL).

Keywords: Long term load forecasting, Simple regression, Libyan network

1 Introduction

Global electricity demand is expected to growth by 85% in 2040 as living standards increase, economies expand and the requirement for electrification of society continues [1]. Electricity demand calculating plays a vital role in load allocation and scheduling for future generation facilities and transmission development. Load demand in a given season is subject to a range of uncertainties, comprising population growth, climate change and economic circumstances. Furthermore, historical data are significance in demand predicting. Load forecasting can be divided into three categories: short-term forecasts, medium-term forecasts and long term forecasts. Short-term forecasts are usually from one hour to one week. They play an important role in the day-to-day operations of a utility such as unit commitment, economic dispatch and load management. A short term electricity demand forecast is commonly mentioned to as an hourly load prediction. Medium-term forecasts are usually from a several weeks to a few months and even up to a one year. They are necessary in planning fuel procurement, scheduling unit maintenance and energy trading and revenue assessment for the utilities. A

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medium-term forecast is commonly referred to as the monthly load forecast. Long-term electricity demand forecasting is a crucial part in the electric power system planning, tariff regulation and energy trading [2]. A long-term forecast is required to be valid from 5 to 25 years. This type of forecast is used to deciding on the system generation and transmission expansion plans. A long term forecast is generally known as an annual peak load [1].

This work offers an uncomplicated technique to forecast the future peak demand for the Libyan electric network. The offered technique might be useful to determine the powerful energy management strategy so as to meet the required load demand at minimum operating cost. In addition, the factors affecting load patterns are presented.

1.1 Factors Affecting Load Patterns

A large number of factors influence the load demand considerably. The effects of all these factors which affect the load need to be studied in order to improve an accurate load forecasting model.

1.2 Economic factor

Several economic factors such as the type of customers such as residential, agricultural, commercial and industrial, demographic conditions, population, GDP growth, national economic growth and social activities etc. can cause a significant variation in the load pattern. These economic factors generally affect the long-term load forecasting.

1.3 Weather Factors

Load forecasting is significantly affected by weather conditions such as temperature (dry and wet temperature), humidity, cloud coverage etc. The most essential weather factor is the temperature. The variations considerably affect the load requirement for heating in winter and air conditioning in summer. Load forecasting also affected by other factors such as humidity especially in hot and humid areas, wind speed and light intensity of the day [3].

1.4 Time and Seasonal Factors

Time factors play an important role in accurate load forecasting. It may cause a considerable change in load pattern. There are following factors;

- Seasonal variation: change of season (summer, winter, rainy and autumn), change of day light hours, change of average temperature, etc.
- Daily variation: different day time and night time consumption
- Weekly cycle: Different weekday and weekend consumption patterns
- Holidays and special days: Load pattern on holidays will be different from that of weekdays and weekend. Special days such as festive days can affect the load.

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1.5 Price Factor

Load forecasting is strongly affected by electricity price. Electrical price which may have a complicated relationship with the system load, it is an important factor in load forecasting. Change in tariff may also change the load pattern.

1.6 Random Disturbances

A random disturbance happens in the power system which may disturb the load pattern considerably. The random disturbances include sudden shutdown or start of industries, wide spread strikes, marriages, special functions etc. [4].

1.7 Other Factors

In addition to all the factors listed above, the load pattern may also change due to geographical condition (urban or rural areas), type of consumers (rural or urban), home appliances sale data, television program (sports, serial etc.) etc. [3]

2 Literature Survey

Generally, long-term load demand forecasting methods can be classified in to two categories: artificial intelligence based methods and parametric methods [5]. The artificial intelligence based methods are further classified in to neural networks [6-10] support vector machines [11], genetic algorithms [12], wavelet networks [13, 14], fuzzy logics [15] and expert system [16] methods. The parametric methods are based on relating load demand to its affecting factors by a mathematical model. The model parameters are estimated using statistical techniques on historical data of load and it's affecting factors. Parametric load forecasting methods can be generally categorized under three approaches: regression methods, time series prediction methods [17]. Traditional statistical load demand forecasting techniques or parametric methods have been used in practice for a long time. These traditional methods can be combined using weighted multi-model forecasting techniques, showing adequate results in practical system. These methods cannot properly present the complex nonlinear relationships that exist between the load and factors that influence on it [18].

3 Simple Linear Regression

A regression model is a statistical procedure that allows a researcher to estimate the linear relationship that relates two or more variables. This linear relationship summarizes the amount of change in one variable that is associated with change in another variable or variables. However, the straight line connecting any two variables X (independent variable) and Y (dependent variable) can be stated algebraically as [19];

$$Y = \beta_0 + \beta_1 X + \varepsilon \quad (1)$$

where β_0 and β_1 are two unknown constants that represent the intercept and slope, known as coefficients, and ϵ is the error term. Given some estimates $\hat{\beta}_0$ and $\hat{\beta}_1$ for the model coefficients, the future values can be predicted as following;

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x \quad (2)$$

where $\hat{y}$ indicates a prediction of Y on the basis of $X = x$. The hat symbol denotes an estimated value.

Let $\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_i$ be the prediction for Y based on the ith value of X. Then $e_i = y_i - \hat{y}_i$ represents the ith residual.

The residual sum of squares (RSS) is defined as;

$$\mathrm{RSS} = e^2{}_1 + e^2{}_2 + \cdots + e^2{}_n \quad (3)$$

The least squares approach chooses $\hat{\beta}_0$ and $\hat{\beta}_1$ to minimize the RSS. The minimizing values can be shown to be;

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (4)$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \quad (5)$$

Where $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$ and $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ are the sample means.

3.1 Assessing the Overall Accuracy of the Model

For making sure that used model is giving a good relationship between the considered variables, the Residual Standard Error (R2) can be calculated as follows [19];

$$R^2 = \frac{\text{Residual sum of sequares}}{\text{Total sum of squares}} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (7)$$

The minimum value for R^2 is 0. This would occur when there is no relationship between the two variables, so that X does not help at all in explaining the differences in values of Y. The maximum possible value for R^2 is 1. This would occur when the two variables are perfectly related, so that the observed values of Y exactly correspond with the predicted values from the regression line, and there are no prediction errors. This would mean a perfect goodness of fit.

3.2 Model Implementation

In this section, a regression model will be performed for forecasting the future peak load for the Libyan network. Data, that used to prepare the forecasted model, are as shown in the Table 1.

According to the historical data available for the peak load as shown in table 1, it is noticed that during the period (2000-2010) the growth rate is different than that in the period (2013-2017) and this due to the situation during the period (2011-2012). This difference of the growth rate that dropped from 5760 MW to 5515 MW and then jumped to 5981 MW, makes it difficult to perform a model that gives an accurate expectation, if the whole period is considered at once, therefore, the period from (2000-2017) is divided according to the growth rate. The first period from (2000-2010), and the second one is (2013-2017), and each period is considered as a case study.

Table 1: *Historical data*

Year	*Population x_i *10^6*	*Peak load (MW) Y_{actual}*
2000	*4.83*	*2630*
2001	*4.93*	*2934*
2002	*5.02*	*3081*
2003	*5.12*	*3341*
2004	*5.22*	*3612*
2005	*5.32*	*3857*
2006	*5.42*	*4005*
2007	*5.53*	*4420*
2008	*5.60*	*4756*
2009	*5.74*	*5282*
2010	*5.86*	*5760*
2011	*5.97*	*5515*
2012	*6.08*	*5981*
2013	*6.20*	*6520*
2014	*6.33*	*6600*
2015	*6.45*	*6750*
2016	*6.57*	*7017*
2017	*6.70*	*7383*

3.3 Case 1 (period 2000-2010)

In this case the historical data for the period (2000-2010) is only considered to achieve a forecasting model. The population is considered an independent variable (x_i) and the historical peak load is a dependent variable Y_i. As the regression model coefficient (β_0, β_1) can be calculated from equations 5 and 6, the forecasting model can be rewritten as following;

$$\hat{y} = -11669 + 0.0029 * x_i \quad (8)$$

From equation 7 the Residual Standard Error (R) also can be calculated;

R^2 =0.996

Where;

$\hat{y}$ = expected peak load

x_i = expected number of the population

As the predicated number of the population is available, the future peak load can be estimated from equation 8 as shown in the Table 2 and figure 1.

Table 2: *results for case 1*

Year	x_i *10^6	Y_{actual} (Mw)	$\hat{y}$ (Mw)
2000	4.83	2630	2.5133
2001	4.93	2934	2.8069
2002	5.02	3081	3.0712
2003	5.12	3341	3.3648
2004	5.22	3612	3.6584
2005	5.32	3857	3.9520
2006	5.42	4005	4.2457
2007	5.53	4420	4.5687
2008	5.60	4756	4.7742
2009	5.74	5282	5.1853
2010	5.86	5760	5.5376
2011	5.97		
2012	6.09		
2013	6.20		
2014	6.33		
2015	6.45		
2016	6.57		
2017	6.70		
2018	6.83		8386
2019	6.96		8768
2020	7.10		9179
2021	7.24		9590
2022	7.38		10001
2023	7.52		10412
2024	7.66		10823
2025	7.81		11263

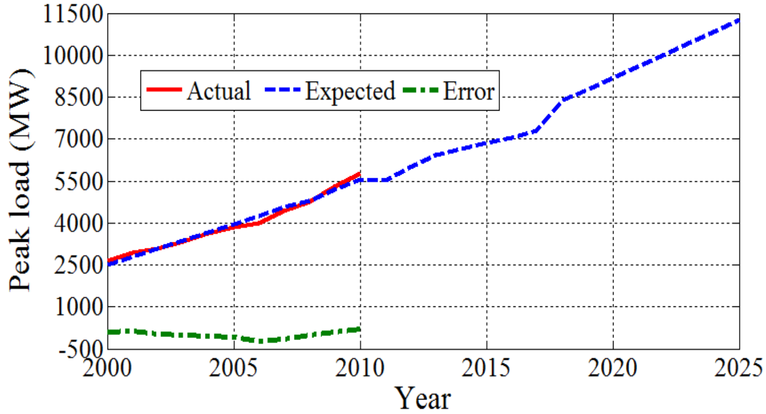

Figure 1: *results for case 1*

3.4 Case 2 (period 2013-2017)

In this case the historical data for the period (2013-2017) is only considered for performing a forecasting model and the same procedure that was used in the first case is done. The forecasting regression model and the R^2 for this case can be written as following:

$$\hat{y} = -4292.6 + 0.0017 * x_i \tag{9}$$

R^2 =0.998

Table 3: *results for case 2*

Year	*x_i *10^6*	*Y_{actual} (Mw)*	*$\hat{y}$ (Mw)*
2013	*6.20*	*6520*	*6.422*
2014	*6.33*	*6600*	*6.6466*
2015	*6.45*	*6750*	*6.854*
2016	*6.57*	*7017*	*7.0614*
2017	*6.70*	*7383*	*7.286*
2018	*6.83*		*7510.7*
2019	*6.96*		*7735.4*
2020	*7.10*		*7977.3*
2021	*7.24*		*8219.2*
2022	*7.38*		*8461.2*
2023	*7.52*		*8703.1*
2024	*7.66*		*8945.1*
2025	*7.81*		*9204.3*

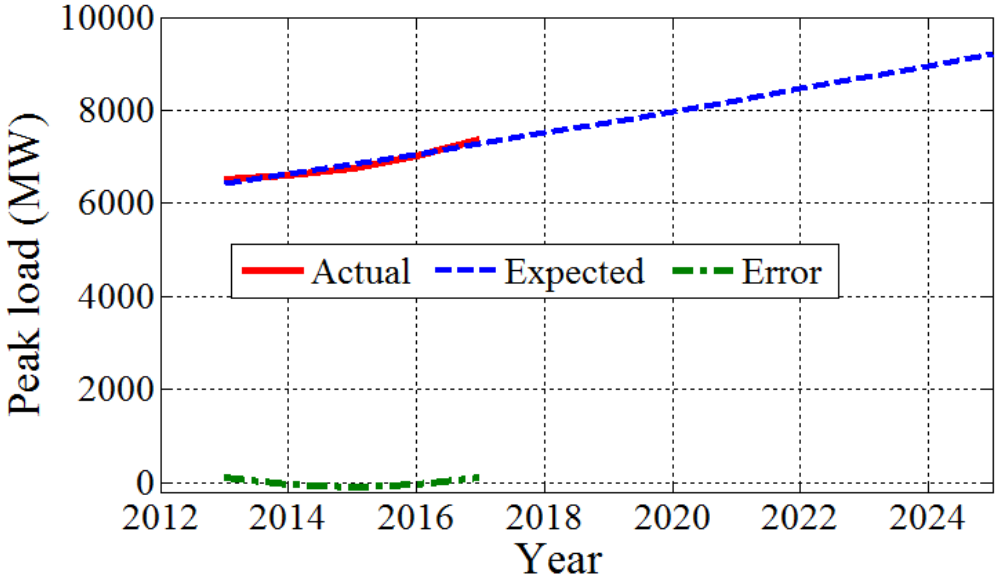

Figure 2: *results for case 2*

4 Discussion of Results

The simple linear regression method was applied to the peak load from 2000 to 2013. After the SLR was explained, it was used in two cases to forecast the peak load from 2018 to 2025. The results attained for case1 are summarized in the Table 1 and illustrated as graphic form in the figure 1. The data used are the annual peak loads and the population number recorded between years 2000 and 2010. It can be seen from results that the expected peak load at 2025 will be about 11263 Mw. On the other side, results for the case 2 are displayed in the Table 2 and demonstrated as graphic form in the figure 2. Data used are the annual peak loads and the population number recorded between years 2013 and 2017. It can also be also seen from the Table 2 that for case 2 the expected peak load will be around 9204.3 Mw.

5 Conclusions

Electric load predicting considers a vital part in the economic optimization and secure operation of electric power systems. It represents the first step in developing future generation, transmission, and distribution facilities. In this paper, the main factors that affect the accuracy of the load forecasts are presented and the annual peak load for seven years ahead is expected for the Libyan electric network. Results demonstrate that proposed method can be used as a good technique for long term load forecasting with minimum error.

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