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Original Article

Short Term Load Forcast - A Case study on Beleza: Eritrea

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Abstract

Electrical load plays a key role in countries' economic development. Generation of energy requires accurate estimation of the load that is in turn accomplished by accurate load forecasting. It plays a key role in balancing energy production and demand. Forecasting of electrical load gives efficient and effective operation of any power system. Many methods are implemented for Short Term Load Forecasting (STLF) considering the effects of temperature, humidity, etc. Load data of Beleza, Asmara, Eritrea, is taken from Eritrean Electric cooperation Asmara for a period of 31days. The load is predicted by using the exponential smoothing techniques including the seasonality effects and day effects on the loads, critical index values and total system loads. The load is forecasted based on the day. Simulation studies are performed in the MATLAB environment.

1. Introduction

Load forecasting provides a solution for power system operating, planning, and marketing [1]. Numerous operating judgments, such as dispatch scheduling of generating capacity, power generators, reliability of the systems, and maintenance scheduling for the generators, are based on load forecasts. As it plays a key role in the electrical industry.

Drastic changes have taken place to operate the power generation industry flat by using diverse forecasting techniques. A variety of techniques have been developed for electricity demand forecasting during the past years [2]. Construction and Engineering firms need accurate forecasting to supply the equipment for the utility industry. Based on the equipment supplies the policymakers have to provide the standards. Forecasting proves the information regarding the total electricity consumption in terms of Kilowatt-hour, Peak demand, forecast for different periods. Basic interest is to predict the load for hourly, weekly, monthly values of the system loads and the maximum loads. Forecasting is classified as Short-term Load Forecasting (STLF), Medium-term Load Forecasting (MLTF), Long term Load Forecasting (LTLF). STLP plays a key role in the power system operation giving ample solutions for decades. STLP provides input data for unit commitment, economic dispatch, optimal power flow, stability assessments and system security [3]. Accurate load forecasting helps the utility industry unit – start-upetc., which saves fuel consumption, service maintenance proportionately, saves money. Whereas lack of forecasting increases the unit cost power kilowatt-hour and leads to power stability problems.

Statistical models are firstly adopted for the load forecasting problem, which includes linear regression models, stochastic processes [14]. STLF also uses the traditional approaches, time series models, Kalman filtering models. Using the traditional approaches, the relationship between variables that affect the load demand and actual demand becomes more complex and inaccuracy. Due to the drawbacks of the traditional

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techniques scientific researchers have given priority to computational intelligence approaches for solving the STLP [4]. These approaches can solve multifaceted problems based on historical data. These approaches are broadly classified into Artificial Neural Networks(ANN)[20-21] like multilayer perceptron (MLP), radial based function (RBF), Support Vector Machines(SVM)[15-18, 20], Fuzzy logic[22-23, 25], ANFIS and hybrid models[24 -26,27]. Researchers proposed the algorithms for estimating the load forecasting using the wavelet transformations by incorporating evolutionary algorithms [19,28].

1. Forecasting Methods:

Short Term Load Forecasting (STLF) is a tedious process, as the load on the system is in time series display non-stationary performance. Moreover, the exogenous variables like weather conditions have a dynamic nonlinear impact on the mapping functions, in addition to historical values [6]. The prominence and intricacy of the forecast analysis inspired many researches on this platform. Time series models for STLF such as ARMA (Auto-Regressive Moving Average) [7] and modified ARMA [8], nonparametric regression [9], Kalman filter [10], and neural network (NN) [9,10] have been presented in the literature. For analyzing the Forecasting techniques methods are mentioned below figure.1, entire load flow process of the paper is presented clearly.

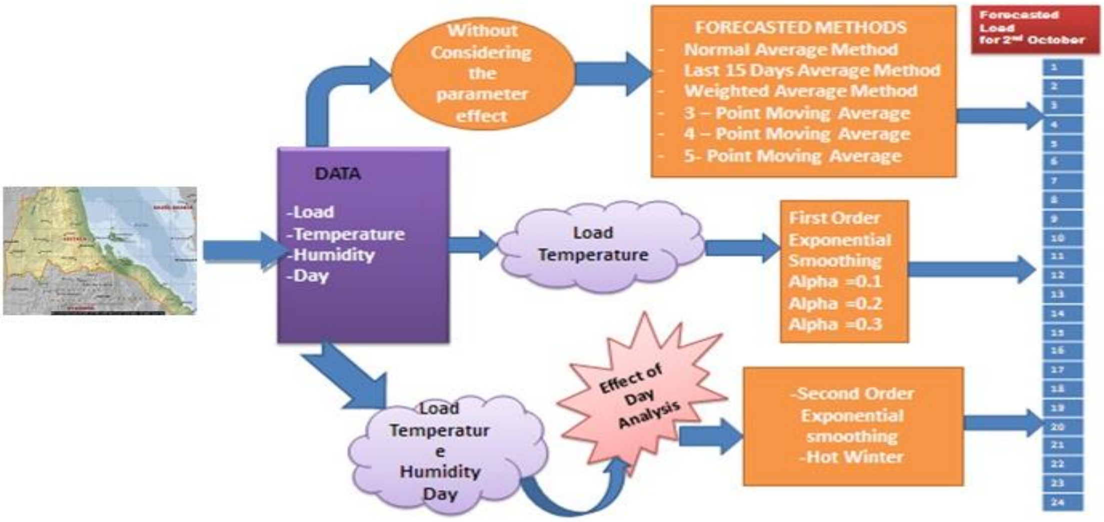


Figure.1 Flow chart for the Load forecast analysis

(a) Simple average: This method is very simple but the accuracy of the results is not good.

(b) Last four values average: In this method forecasted values is based on the last four values average

(c) Weighted Moving Average: The stint ‘moving’ is used because each time a new data value turns out to be available for the time series, it replaces the older data. The weighted average method provides some accuracy based on previous methods. For each value provides some weights, the last values give more weights to get good accuracy results.

$$F_t = \frac{\sum_{i=1}^{n} A_{t-i}}{n} \quad (1)$$

Where F_t = Forecast time period;

A_{t-i} = Actual value in period;

n = number of periods

(d) Exponential Smoothing: In this method, load forecasting is based on the time series of the historical data of the load consumed by the consumers. Decreasing weights are used for the previous observations of the historical data. Highest weighted values are given for the recent values [5]. Types of exponential smoothing are First-order, second-order, and higher-order exponential smoothing and hot winters mechanism.

(i) **First-order exponential smoothing:** First order exponential smoothing uses a recursive equation which is a linear combination of current observation and smoothed observation of the previous observation. Previous observation contains T estimated time.

$$Y_{T+1} = \propto Y_T + (1 - \propto) * Y_T \quad ..(1)$$

Where Y_{T+1} is the estimated load value for the time period T+1

Y_T is the actual load data for the previous time period T

$\propto$ is the smoothing factor between [0,1]. Best values are 0.1 to 0.3

(ii) **Second-order exponential smoothing:** For conferring time series through trend analysis first-order exponential smoothing was extended by holt. Second-order time series adjusts the trend component to be linear [5]

$$Y_{T+h} = A_t + h * B_t \quad .....(2)$$

Where parameters of (eq.2) are expressed in eq3 and 4

$$A_t = \propto Y_t + (1 - \propto)(A_{t-1} - B_{t-1}) \quad .....(3)$$

$$B_t = \propto Y_t + (1 - \propto)(A_t - A_{t-1}) + (1 - \beta)B_{t-1} \quad .....(3)$$

Where A_t is the value of the intercept.

B_t is the value of the slope h is the time horizon (For one step ahead forecasting h is 1)

$\propto, \beta$ are discount factors {0,1}

(iii) **Holt-Winters for seasonal time series:** Time series data exhibit variations based on the seasonal patterns, cannot be modeled using the polynomial models. These seasonal models are made using the linear trend model. Two types of seasonal adjustments are used additive and multiplicative model. Comparing two models multiplicative model gives more accuracy and smoothing results in the linear trend forecasting [5].

$$Y_{t+h} = [(A]_T + hB_t)S_{t-p+h} \quad ...(4)$$

Where h is the time horizon

Y_{t+h} is the forecasted value

A_T is the level of the time series

B_T is the trend of the time series

S_{t-p+h} is the seasonal adjustment

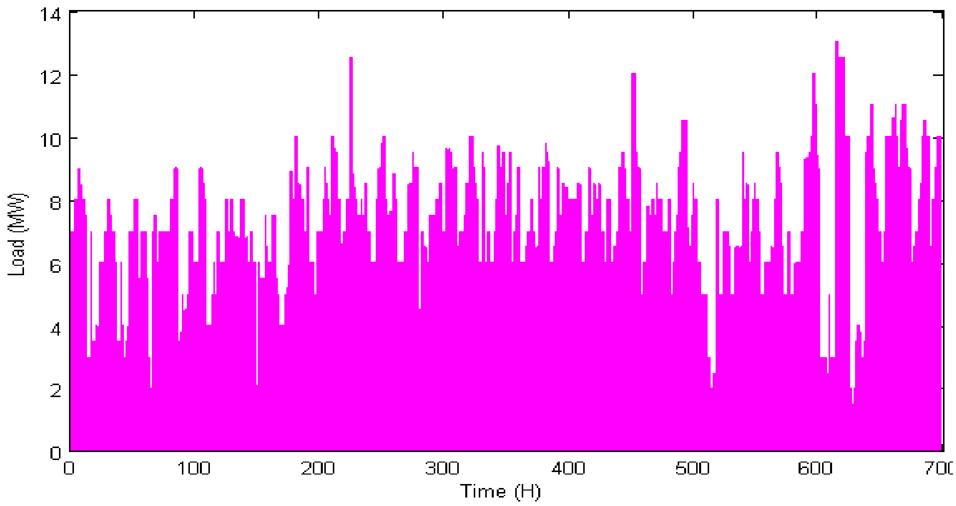
(e) Scaling of the input and output data: The collected data variables have different ranges. To confirm a smooth and to avoid the potential convergence all variables are scaled in the range [0,1].

$$Y_s = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \quad ....(5)$$

2. Case study and Data Collection

For the Analysis Data is collected from the Eritrean Electrical Corporation (EEC), Asmara, Eritrea. African country Eritrea is bounded with the Redsea, on the southeast by Djibouti, on the south and west by Ethiopia, and on the north and northwest by Sudan. The EEC is located in the capital city Asmara. Hrigigoas the main generating site and Beleza as a supplementary site major for the Eritrean Electricity production. The EEC maintains the grid system which connects the Hrigigo-Ghnda-Ghrar-Dekmare-Asmara Center-Beleza-Keren-Gurgusum-Tsada-Denden. Data is collected from the EEC headquarters which is located in Asmara.

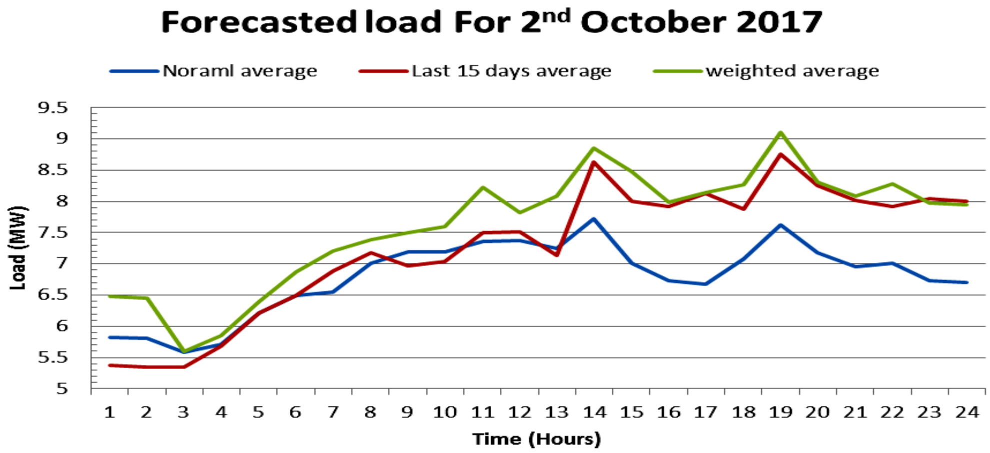
The analysis load data of Beleza is taken for a period of one month September- 2017 every one hour. The temperature data is considered as average value for the whole day for one month. Graph.1 shows the load profile of the Beleza which is collected from the EEC.



Graph.1 Actual load profile of September 2017 of Beleza Eritrea.

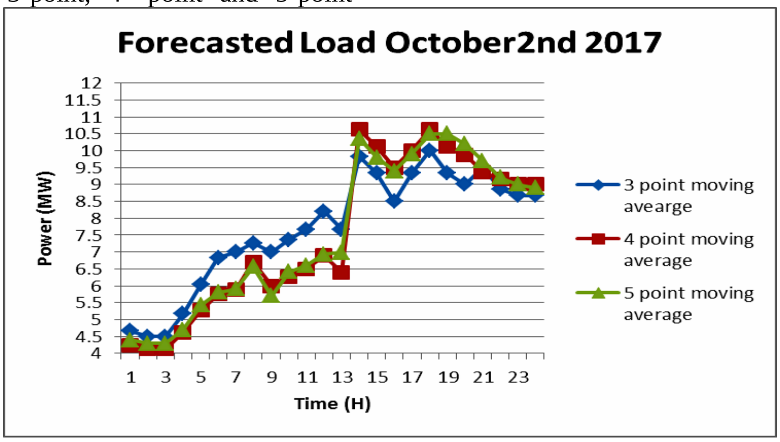
3. Result Analysis:

Forecasting the electricity load data has significance reasons like load for the next 30 min to year, market demand, cost analysis, economic operation e.t.c. The load is for the 2nd October 2017 by considering the one-month load values of 1st -30th September and 1st October. The analytical results are presented below for different methods. The basic methods like moving average, weighted average and Last 15 days average methods are used to estimate the load demand on 2nd October, and graphical results are presented in Graph.2.



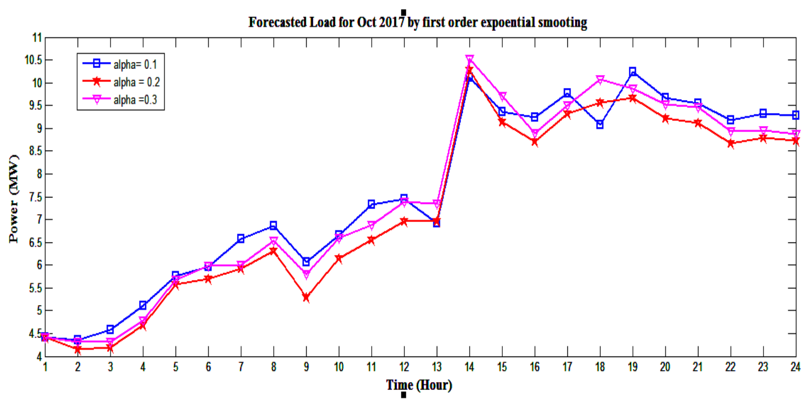
Graph.2 Forecasted load for the Beleza by Normal, weighted and last 15 days average.

The forecasted load for the next day is calculated by moving averages. 3-point, 4- point and 5-point averages of last data of the time series data. Results are presented in the Graph-3



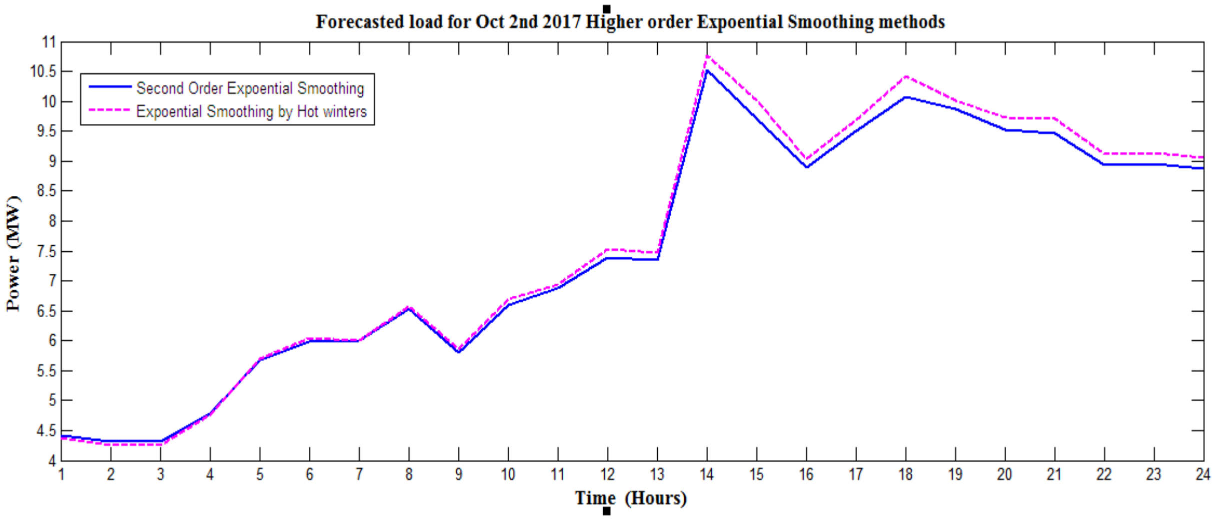
Graph-3 Forecasted load for the Beleza by 3,4,5 – point moving averages

Graphical results of the forecasted load by using the first-order exponential smoothing for different smoothing constant values, α of 0.1, 0.2 and 0.3 are shown in the graph-4.

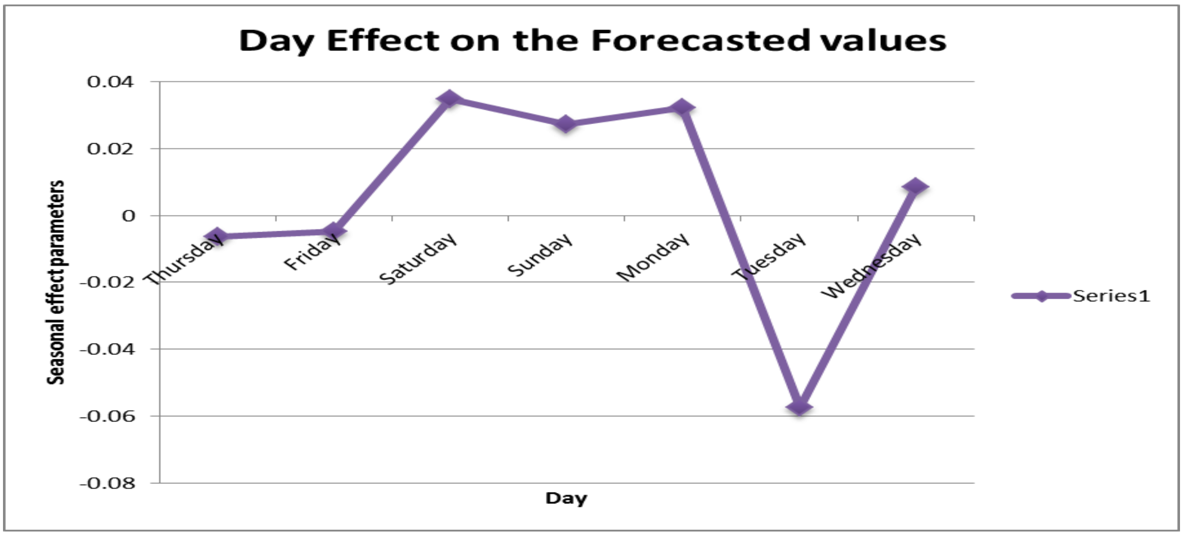


Graph-4 Forecasted load for the Beleza by first-order exponential smoothing

Normal average methods, first-order exponential smoothing methods will not provide the accuracy in the forecasted results. For the better accurate results, second-order exponential methods are used. In performing the higher-order exponential smoothing methods, the effect and the seasonality parameters are considered and presented in graph.6. The day parameter effect influences the load estimated values. Results for the higher-order exponential smoothing and hot winters model are shown in the graph-5. The graphical results shown from graph-2 to 5 are all the forecasted results for the load center Beleza for 2nd October 2017. Among results presented by all the methods the Hot-winters model is having good accuracy.



Graph-5 Forecasted load for the Beleza by Higher-order exponential smoothing



Graph-6 Day parameter effects on the forecasted values

4. Accuracy Measurement:

Short term Load forecasted (STLF) accuracy is measured by using the Statistical analysis like Mean Absolute Percentage Error (MAPE), Mean absolute deviation (MAD) and Mean Squared Error (MSE) [11]. MAPE measures the accuracy of time series close-fitting values [12]. For prediction of accuracy of each model MAPE is used and is defined by formula

$$MAPE = \frac{\frac{\sum |A_t - F_t|}{A_t}}{n} * 100 \quad ....(6)$$

Overall forecast error is measured by Mean absolute deviation (MAD)[13]. It represents the difference between forecasted and actual load and is defined by a formula

$$\text{MAD} = \frac{\sum |A_t - F_t|}{n} \quad \text{....(7)}$$

Mean Square Error (MSE) gives an average of the squares of the difference between the actual value and forecasted value and is defined by a formula

$$\text{MSE} = \frac{\sum (A_t - F_t)^2}{n - 1} \quad \text{....(8)}$$

An accurate Short term load forecasting (STLF) provides a path to better economic operations and decision making to enhance the power system security. Several Load forecast studies resolved 1% reduction in mean absolute percentage error (MAPE) of the STLF decreases the generation variable cost by 0.1-0.3% if the MAPE is varied in the range of 3-5%. Table.1 shows the MAPE and MSE values of forecasted methods, seeing the tabulated results the MAPE and MSE value is less for Exponential smoothing with Hot winters model.

Table.1 MAPE and MSE values for different forecasted methods for the 2nd of October 2017.

Forecasted Methods		MAPE	MSE
First order exponential smoothing	***Alpha=0.1***	2.18486159	0.011147226
	Alpha =0.2	2.12286813	0.0109
	Alpha =0.3	2.085483585	0.010310205
Second-order exponential smoothing		2.03548359	0.010310205
Exponential smoothing with Hot winters model		1.95533787	0.01021

MAPE, RMSE, MAD is calculated for each and every hour for the Exponential smoothing with Hot winters model is presented below. In order to present the best optimal values, the simulation is ruined for Hot winters model by considering the discount factors starting from 0 to 1 with an increment of 0.02. The MSE values have been calculated for every hour. On comparing the MAPE values from the table.1 and table.2, calculated MAPE value for entire day is MAPE (Hot winters model for whole day) is 1.955 and the average of the MAPE (hour-1 to hour-24) the MAPE is 1.79.

Table.2 MAD, MSE, RMSE, and MAPE values for each hour of the 2nd October 2017 for the Hot winters model.

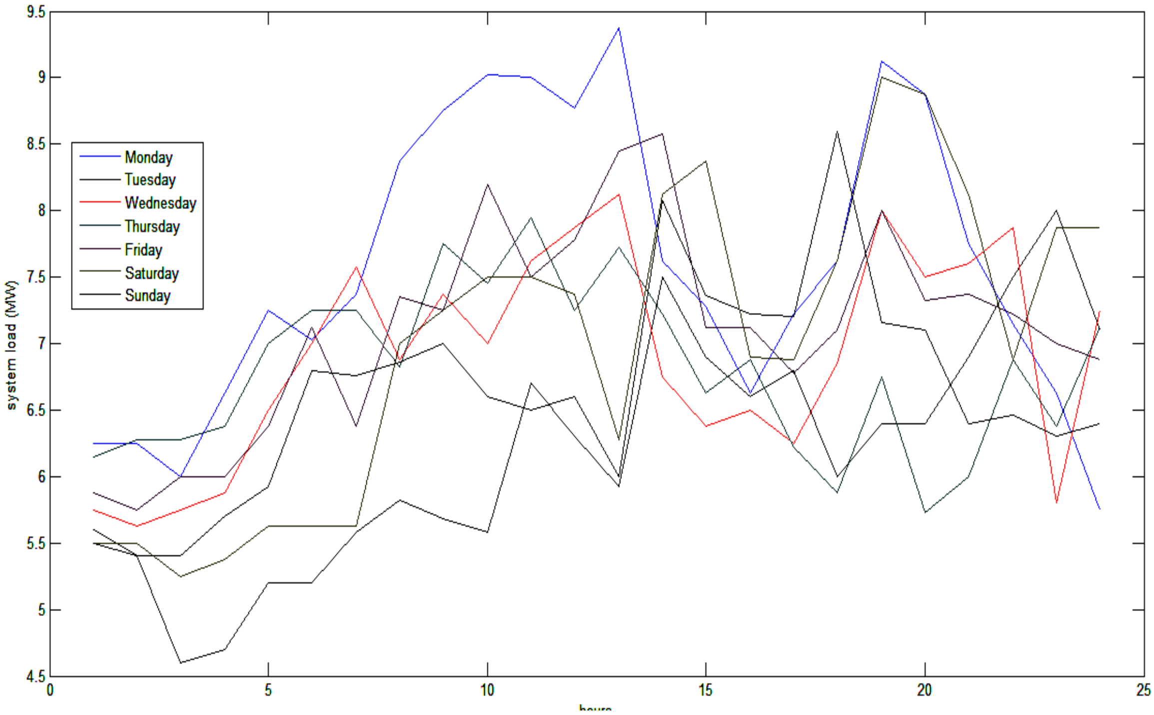
	Hour-1	Hour-2	Hour-3	Hour-4	Hour-5	Hour-6	Hour-7	Hour-8
MAD	0.164218	0.166578	0.169112	0.167278	0.172888	0.156429	0.194246	0.183129
MSE	0.014883	0.023529	0.028299	0.005265	0.003214	0.041114	1.16E-05	0.023482
RMSE	0.121997	0.153392	0.168224	0.072559	0.056695	0.202766	0.003407	0.153239
MAPE	0.36794	0.51079	0.58513	0.18297	0.06968	0.04696	0.00624	0.0404

	Hour-9	Hour-10	Hour-11	Hour-12	Hour-13	Hour-14	Hour-15	Hour-16
MAD	0.157779	0.161309	0.185161	0.159829	0.161537	0.201518	0.144554	0.212168
MSE	0.026592	0.081566	0.041887	0.190388	0.175309	0.587658	0.880698	0.173633
RMSE	0.16307	0.285597	0.204663	0.436334	0.418699	0.766589	0.938455	0.416693
MAPE	0.02696	0.30271	0.05128	1.1202	1.00109	4.49975	7.12147	0.98793

	Hour-17	Hour-18	Hour-19	Hour-20	Hour-21	Hour-22	Hour-23	Hour-24
MAD	0.157779	0.128653	0.237718	0.201884	0.175559	0.192487	0.187428	0.186495
MSE	0.026592	1.191189	0.202176	0.345335	0.524106	0.284639	0.31823	0.307308
RMSE	0.16307	1.091416	0.449639	0.587652	0.723952	0.533516	0.564119	0.554354
MAPE	0.02696	9.95164	1.21418	2.3979	3.94081	1.88817	2.16911	2.07743

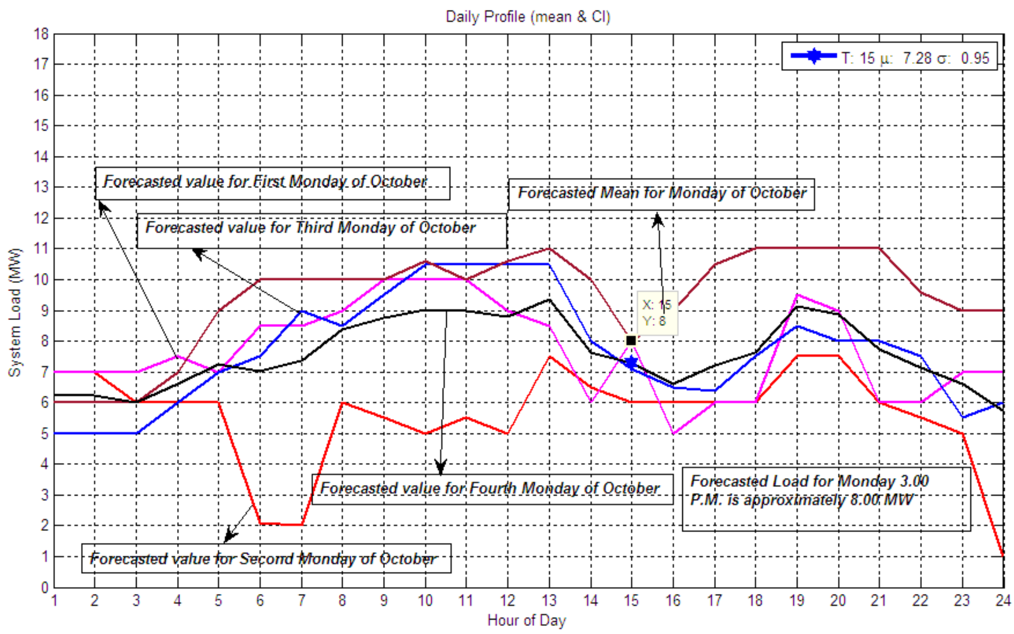
week from Sunday to Saturday is shown in the below graph.7.

The total system loads for the month are presented for weekdays. The forecasted load of October month load is presented in the below graph for each

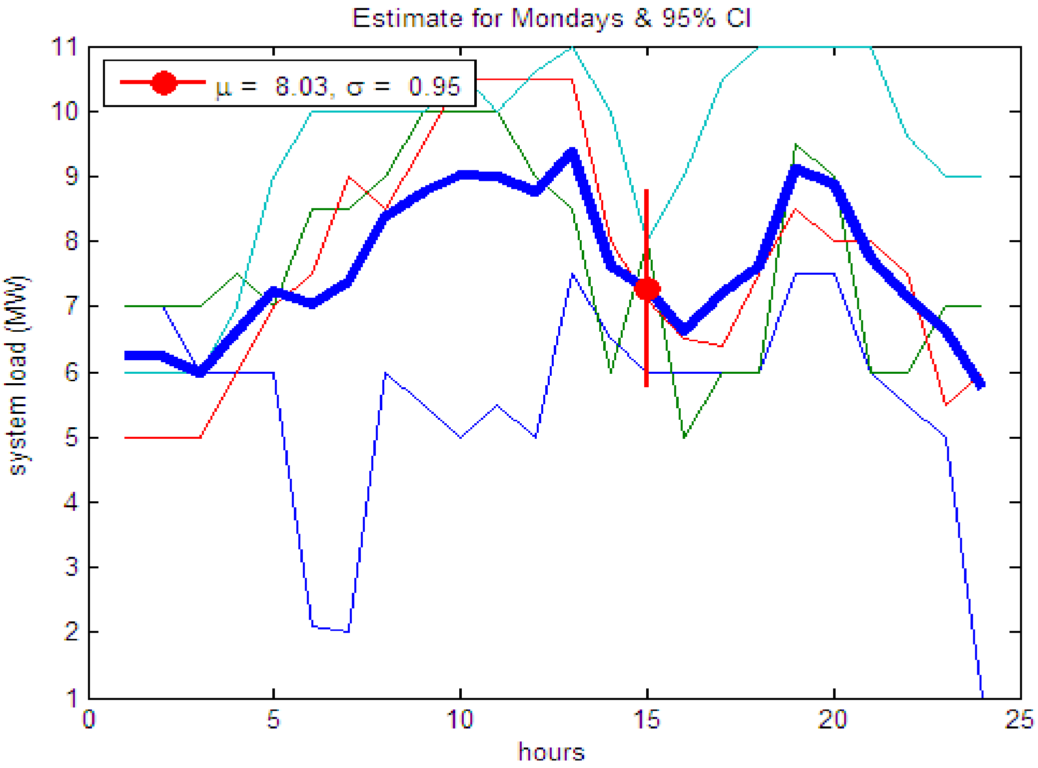


Graph.7 Forecasted average loads of Beleza for October for all weekdays.

The load is forecasted for every day based on the confidence intervals for every day. Forecasted values for every Monday of October 2017 are shown in the below graphs based on 95% confidence intervals at the particular time periods 3.00 p.m.The estimated total system loads on Mondays for 95% critical index values are shown in the below graph.8. The Mean value of the forecasted load is 8.03 MW and the standard deviation is 2.70 MW. Graph.9 shows the forecasted load for the first Monday of October at evening 3.00 P.M. The average load forecasted at 3.00 P.M is 8.03 MW.



Graph.8 Forecasted average loads of Beleza October on all Mondays.



Graph.9 Forecasted load for the October 2nd Monday.

The Total forecasted system load for different weekdays for October 10.00 A.M are presented below in the table

Table.3 Total average system loads for October Month.

		Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
System Load		8.03	5.58	6.60	7.45	8.20	7.50	7.00
System Load critical Index (95%)	Low	4.7348	1.5313	5.7008	5.8775	6.2339	2.6823	3.7080
	High	13.3152	9.6287	8.2992	9.0225	10.1661	12.3177	9.4920

Conclusion:

In this paper, the Exponential smoothing technique is successfully implemented for the STLF. Exponential smoothing is seldom used for the STLF because of the poor results associated with fitting techniques. However, the model proposed in the paper gives better performance. Loads are forecasted using different techniques and results are compared. Load on October 2nd for the Beleza is forecasted and acquire good accuracy, Load is forecasted for the entire month of October considering the day and seasonality effects. Considering the critical index value at 95%, the load forecasted on all the days is also presented. Accuracy is estimated using the statistical tools. The absolute errors for each hour are presented clearly.

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