Least Square Regression Based Integrated Multi-Parameteric Demand Modeling for Short Term Load Forecasting

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ABSTRACT

Nowadays, due to power crisis, electricity demand forecasting is deemed an important area for socioeconomic development and proper anticipation of the load forecasting is considered essential step towards efficient power system operation, scheduling and planning. In this paper, we present STLF (Short Term Load Forecasting) using multiple regression techniques (i.e. linear, multiple linear, quadratic and exponential) by considering hour by hour load model based on specific targeted day approach with temperature variant parameter. The proposed work forecasts the future load demand correlation with linear and non-linear parameters (i.e. considering temperature in our case) through different regression approaches. The overall load forecasting error is 2.98% which is very much acceptable. From proposed regression techniques, Quadratic Regression technique performs better compared to than other techniques because it can optimally fit broad range of functions and data sets. The work proposed in this paper, will pave a path to effectively forecast the specific day load with multiple variance factors in a way that optimal accuracy can be maintained.

Key Words: **Load Modeling, Short-Term Load Forecasting, Regression Technique, Least Square Error, Load Forecasting Error.**

1. INTRODUCTION

Electric load forecasting has progressively become the most critical factor across the energy deficit countries and especially in Pakistan to overcome the electric supply and distribution issues [1] that must be effective across wide range of time intervals. Accurate load forecasting alleviates a lot of challenges and supports in making proper decisions including purchasing and generating the electrical power, load switching and infrastructure development [2]. However, optimized load forecasting is not a trivial issue because load series is dynamically complex and is dependent upon various nonlinear factors [3]. The electric usage is flexible pattern correlated with diverse factors like demographic dynamics [4], seasonality variable [5], metrological weather variance vectors like temperature and humidity [6], weekdays/ weekends or public holidays [7], special days [8], peak hours or specific timing [9], electricity price [10], customer's class [11] etc. The entire electric usage approaches

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establishes a link between dependent variable and established predictors. Recently, the work reported in [12] is related to time spectrum with categories defined as short, medium and long term forecasting. These approaches are being used for different customary applications with different time span ranging from one hour to many years.

STLF is customarily planned for energy management systems with realistic economic saving along with reliable power systems operation and is widely accepted for narrow time intervals (for example few hours to few days) [13]. Unlike STLF, MTLF (Medium Term Load Forecasting) is used for supply availability schedules, systematic monitoring and maintenance mechanism that require one to few weeks' time interval [14]. On the contrary, LTLF (Long Term Load Forecasting) mandates the wide spectrum system plans and policy formations which are carried from few months to several years [15]. Due to dynamic nature of the STLF, wide range of models and techniques are reported in the literature. For example-time series models [16], statistical regression models [17], exponentially weighted models [18], support vector machine regression approach [19], ANN (Artificial Neural Network) approach [20], Autoregressive Integrated Moving-Average model [21], multi-wavelet transform [22], particle swarm optimization [23], Kalman filtering algorithm [24], and different integrated models [25] to improve operation system accuracy and efficiency.

In all the reported works, proposed models are classified either as parametric or non-parametric models. In load forecasting, optimal algorithms often requires the understanding of underlying densities to predict the unknown information based on data density estimation. If a particular density form is known or assumed according to data or information, then parametric estimation is used, on contrary, if no prior or very little scattered information is available than non-parametric estimation is the choice [26].

The parametric approach formulates a statistical model of load by examining qualitative relationships between the load and load affecting factors, by using CPL (Critical Peak Load) techniques to forecast the load on the basis of well-defined historical information. The assumed model parameters are then estimated from historical data and the adequacy of the model is verified by analysis of model residuals, i.e. forecast errors. In order to obtain high forecast accuracy, elaborate models are developed which are often data dependent and may not perform well when applied in another utility. In PLM (Parametric Load Models), forecasted load is linear function of predicted variables which is generally estimated through linear regression type statistical approaches.

The non-parametric approach specifically searches a collection of historical observations for records similar to the current conditions and uses these to estimate the future state of the system. In NPLM (Non-Parametric Load Models), data can be extracted on the basis of CLP to model the future trends. The NPLM are mostly non-linear function of predicted variables, generally estimated through some sort of learning and supervisory systems.

In this research work, we have proposed an integrated approach by considering the both parametric CPL and non-parametric CLP (Critical Load Pattern) for linear and non-linear characteristics of load respectively. With the proposed approach, hour by hour (24 hours) recorded temperature and load data of selected area (i.e. 132kV Qasimabad Grid Station at HESCO (Hyderabad Electric Supply Corporation), Pakistan, for specifically selected days was collected from the original source. Based on acquired temperature and load data and employing least square error approach, the load model was developed and forecasted for two parametric (i.e. Linear and Multiple linear) and two non-parametric (i.e. Quadratic and Exponential) approaches. In this work, we have taken rigorous approach to validate the model by taking only specific days samples to estimate the load forecast. Finally the results were validated by using the recorded data and MSE (Mean Squared Error) was calculated for actual load and forecasted load.

The rest of paper proceeds as follows. In Section 2, we have the proposed the multi-parametric STLF model based on LSE (Least Square Error) approach, followed by case study example of 132kV Qasimabad Grid Station in Section 3. The flow chart of proposed model is discussed in Section 4, followed by Results and Discussion in Section 5. In Section 6, conclusion and point to future work is presented.

2. PROPOSED LEAST SQUARE REGRESSION BASED MULTI-PARAMETRIC DEMAND MODELING FOR STLF

Off-course, load forecasting is a non-trivial task due to its non-linear nature specifically affected by time of the day and weather conditions (temperature, humidity etc.). The time and weather dependency of the load reflects the variation in daily load pattern which may vary for different week days and seasons. For instance, the load at a given hour is dependent on load at the same hour on the previous day and previous week and so on, as many important exogenous variables need to be pondered. In constructing a load forecasting model, a mathematical relation is established between the measured load and various factors of influence. The proposed model must contain several coefficients, with values to be determined, that quantify the magnitudes of each influence. The coefficient values are chosen such that the overall error between model estimates and actual measured loads is minimized. To model and forecast the load, statistical regression approach is still a popular being the predictable method to determine the best value of an unknown quantity relating to one or more sets of observations that best fit a set of data.

Regression technique is a common statistical approach to estimate the future demand. In electrical engineering, regression techniques are used to model the electric load as a function of load consumption in relationship with different dynamics like seasonal patterns, meteorological changes, day type, and consumer social class etc. In regression technique, correlation between a dependent variable for example y and one or more independent variables $x_1, x_2, \ldots, x_k$ is modeled for analysis. The dependent variable is the response variable, while independent variables are called as descriptive or predictor variables. The precise aim of regression analysis is to determine a function that defines the accurate relationship between projected parameters in way that based on independent variables, predictable values of dependent variables can be calculated accurately.

Different regression based techniques are reported in literature survey to forecast the load like linear [27], multiple linear [28], polynomial [29], support vector [30], quadratic [31], exponential regression [32] etc. Most of the theses regression approaches are used as standalone techniques for specific domains and applications to forecast the load. In this paper by using least squares regression approach, an integrated multi-parametric model is proposed to model and forecast the hour by hour load of specifically selected days for selected area. The effect of hour by hour temperature is also deliberated to reflect the model accuracy.

Least Squares Regression method is the optimal approach when model's form is known already and only interest is to find its parameters. The least-squares approach minimizes the difference of the independent estimators of the coefficients in a way that the estimated error is minimized to zero, as given in Equation (1) [33].

$$S_e = \sum_{i=1}^{n} \left(y_i \text{, Real Value - } y_i \text{, Approximate Value}\right)^2 \quad (1)$$

In Equation (1), n is the number of sample data, $y_{i,\text{real value}}$ is the recorded data (i.e. real time), $y_{i,\text{approximate value}}$ is the predictable value based on specific function or approach used and S_e is the sum of the squared projected error. In this approach, the variable S_e is differentiated to each coefficient in a way that error may be normalized to zero. By this approach, we have proposed an integrated model to forecast the specific day load by developing four different regression equations, two for linear (linear and multiple linear) and two for non-linear (quadratic and exponential) characteristics of load and temperature variance.

2.1 The Linear Regression

The linear regression technique characterizes the dependent variable according to the quantified independent variable. With this approach, the change in independent variables is unfortunately random because this is not as per initial setup. For load forecasting, the dependent variable is usually demand according to historical trends which is then correlated with independent variables which are modeled according to exogenous factors like seasons and temperature. The simple linear regression model with linear correlation between the dependent and independent variables y and x is given in Equation (2) [34].

$$y = a + bx + e_f \quad (2)$$

Whereas a and b are regression coefficients, and e_f is the random forecast error. Slope coefficients appraise the changes in the dependent variable with respect to independent variable; as such this will help to easily predict the future values of the dependent variable with minimum possible error. In order to attain zero error, by applying the least squares errors method in Equation (2), following relationships can be established, as given in Equations (3-4) respectively.

$$y = a + b\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i + e_f \quad (3)$$

where i = 1,2,3.n.

$$a\sum_{i=1}^{n} x_i + b\sum_{i=1}^{n} x_i^2 = \sum_{i=1}^{n} x_i y_i + e_f \quad (4)$$

Here,y, x and n are historical peak loads, the specific selected days for input data and the total number of days aimed for forecasting respectively. The coefficients a and b relates to hourly recorded temperature and load of selected day which can be calculated from the Equations (3-4) and replaced in Equation (2) to perform the load forecasting.

2.2 Multiple Linear Regressions

In multiple linear regressions, the combination of the independent variables that best outfit the response is acquired. In this approach, the dependent variable y is a function of more than one independent variable, which form's the relationships among the variables through the matrix equations so that any additional variables can be accommodated, if needed. This relationship is given below in Equation (5).

$$y = a_0 + a_1 x_1 + a_2 x_2 + \ldots.. + a_n x_n \quad (5)$$

Here y represent the electrical load, a_0, a_1 and a_2 are unknown regression coefficients, whereas x_1 and x_2 are explanatory influenced exogenous variables. The unknown coefficients a_0, a_1 and a_2 can be solved through multiple regression approach by reducing the sum of the squares of the projected errors. The explanatory influenced exogenous variables (x_1 and $x_{2+.....}$) variables are recognized according to the correlation analysis of independent variables with the dependent variable (y).This approach shows a plane in the space with three dimensions which can be expressed as given in Equation (6).

$$y = a + bx_1 + cx_2 \tag{6}$$

In Equation (6), a, b and c are regression parameters relating the mean value of y to x_1 and x_2 , where c represents any exogenous factor.

For the simplicity, these equations can be reproduced in matrix notation as given in Equation (7).

$$y = x\beta + e \tag{7}$$

Where terms y,x,β and e are defined through Equations [8-11] respectively.

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \tag{8}$$

$$x = \begin{bmatrix} 1 & x_{11} & \cdots & \cdots & x_{1n} \\ 1 & x_{12} & \cdots & \cdots & x_{2n} \\ 1 & x_{n1} & \cdots & \cdots & x_{nm} \end{bmatrix} \tag{9}$$

$$\beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix} \tag{10}$$

and

$$e = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix} \tag{11}$$

When the least squares method is applied in defined matrix notations (to achieve zero offset error), the fitted regression model is obtained as given in Equation (12).

$$\begin{bmatrix} n & \sum_{i=1}^{n} x_{1i} & \sum_{i=1}^{n} x_{2i} \\ \sum_{i=1}^{n} x_{1i} & \sum_{i=1}^{n} x_{1i}^2 & \sum_{i=1}^{n} x_{1i}.x_{2i} \\ \sum_{i=1}^{n} x_{2i} & \sum_{i=1}^{n} x_{1i}.x_{2i} & \sum_{i=1}^{n} x_{2i}^2 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} y_i \\ \sum_{i=1}^{n} x_{1i} y_i \\ \sum_{i=1}^{n} x_{2i} y_i \end{bmatrix} \tag{12}$$

By solving the Equation (12); b and c parameters are calculated; where y is the real system load demand, x_{i1} is the specified season, x_{i2} is ambient temperature, n is the hour of day selected to forecast the load. By replacing the regression parameters in Equation (11) the peak load forecasting is performed.

2.3 The Quadratic Regression

The quadratic regression model can be defined through parabolic, intercept, linear and squared terms. In a generalized form, the parabolic function as given in Equation (13) is used.

$$y = a + bx + cx^2 \tag{13}$$

The a, b and c coefficients of the parabolic function can be obtained from Equation (14) which is written in matrix form.

$$\begin{bmatrix} n & \sum_{i=1}^{n} x_i & \sum_{i=1}^{n} x_i^2 \\ \sum_{i=1}^{n} x_i & \sum_{i=1}^{n} x_i^2 & \sum_{i=1}^{n} x_i^3 \\ \sum_{i=1}^{n} x_i^2 & \sum_{i=1}^{n} x_i^3 & \sum_{i=1}^{n} x_i^4 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} x_i \\ \sum_{i=1}^{n} x_i y_i \\ \sum_{i=1}^{n} x_i^2 y_i \end{bmatrix} \tag{14}$$

The load forecasting is performed by replacing the calculated coefficients in Equation (13).

2.4 The Exponential Regression

In this approach, the trend equation is formed by using an exponential function as given in Equation (15).

$$y = ab^x \tag{15}$$

By writing the Equation (15) in logarithmic form and then applying the least squares approach, Equations (16-18) are formed.

$$\log y = \log a + x \log b \tag{16}$$

$$\sum_{i=1}^{n} \log y_i = n \log a + \sum_{i=1}^{n} (x_i \log b) \tag{17}$$

$$\sum_{i=1}^{n} (x_i \log y_i) = \sum_{i=1}^{n} (x_i \log a) + \sum_{i=1}^{n} (x_i^2 \log b) \tag{18}$$

Since the Equation (16) is linear, by applying linear trend analysis, a and b coefficients are found as given in Equations (19-20) respectively.

$$\log a = \frac{1}{n} \sum_{i=1}^{n} \log y_i \tag{19}$$

$$\log b = \frac{\sum_{i=1}^{n} x_i \log y_i}{\sum_{i=1}^{n} x_i^2} \tag{20}$$

By replacing a and b coefficients in Equation (15) the peak loads can be easily predicted.

3. 132KV QASIMABAD GRID STATION: CASE STUDY EXAMPLE

To model the load, 132kV grid station of HESCO named as Qasimabad Grid Station is selected as a case study. To forecast the load, the proposed model is trained for load and temperature data for 365 days of 2012 year as an input data sample, then four random days were selected (1st January, 1st April, 1st July and 1st October, 2012) to represent every seasonal quarter as an output data sample.

The historical recorded hour by hour load demand and temperature of 132kV Qasimabad Grid Station for selective four days are shown in Fig. 1. The Fig. 1(a-d) represents the selected days i.e. 1st January 2012, 1st April 2012, 1st July 2012 and 1st October 2012 respectively.

It is quite evident from graphs that temperature directly affects the load demand. Secondly, load demand has certain on and off peaks that makes the window of DSM (Demand Side Management) options and strategies.

4. PROPOSED MODEL FLOWCHART

In this work, to forecast the selected day load, we have used least square approach to model the regression techniques to outfit the independent variables based on dependent variables by modeling the effect of hourly temperature. The flowchart of the proposed algorithm is shown in Fig. 2.

In this work, we have only validated our model for four selected days which belongs to past historical days of 2012 year selected as output data samples. Since the proposed model is trained for 365 days with 24 samples (hour by hour) for each day, making 8760 samples in total. So recorded load and temperature data was sampled in different clusters and then they were grouped to have sorted data. After grouping of data, load and temperature coefficient were premeditated. Then these coefficients values were set as the input parameter in proposed model for different techniques to forecast the load for specifically selected days. Finally the achieved load forecasting values for each regression technique was compared with actual recorded load. The compute the load forecasting MSE was used.

5. RESULTS AND DISCUSSION

To validate the proposed algorithm least square approach is used to model the four different regression techniques for four randomly selected days of the year. The selected day's load forecast is modeled by considering the hour by hour effect of temperature.

5.1 Hour by Hour Actual Recorded vs. Forecasted Load

The load forecasting results attained for four proposed regression techniques i.e. simple linear, multiple linear, exponential, quadratic regression in comparison with the actually recorded load are shown in Fig. 3. The Fig. 3(a-d) represents the four selected days respectively. The achieved Load forecasting results are very much symmetric with actual recorded load curve. The few visible spikes of load forecasting differences with different days and timing are due to temperature coefficient variance.

5.2 Load Forecasting Error

Load forecasting error is normally estimated through MSE, one of the popular error estimation metrics [35]. The error estimation methods are scale-dependent approaches; they simply compare models forecasting errors for defined variables. MSE can be defined as given in Equation (21).

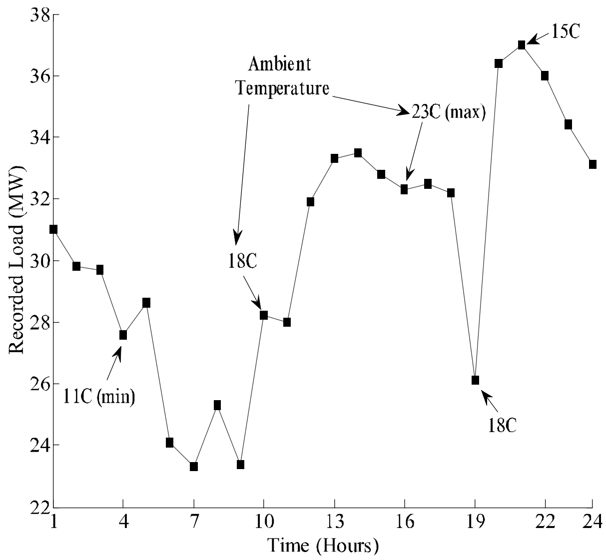


FIG. 1(a). 132KV QASIMABAD GRID-HESCO JANUARY 01, 2012

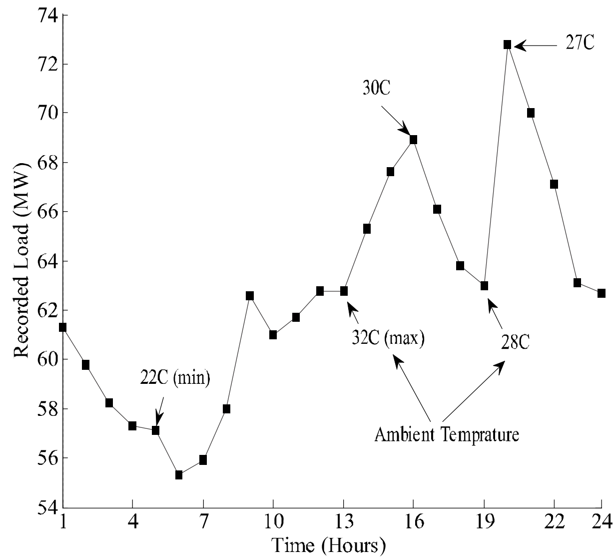


FIG. 1(b). 132KV QASIMABAD GRID-HESCO APRIL 01, 2012

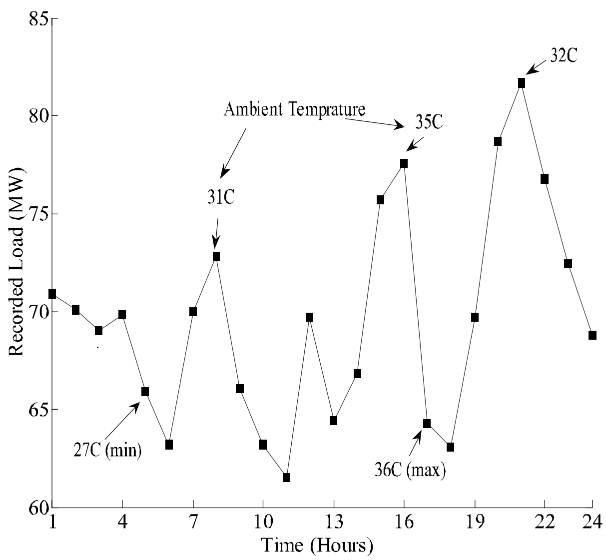


FIG. 1(c). 132KV QASIMABAD GRID-HESCO JULY 01, 2012

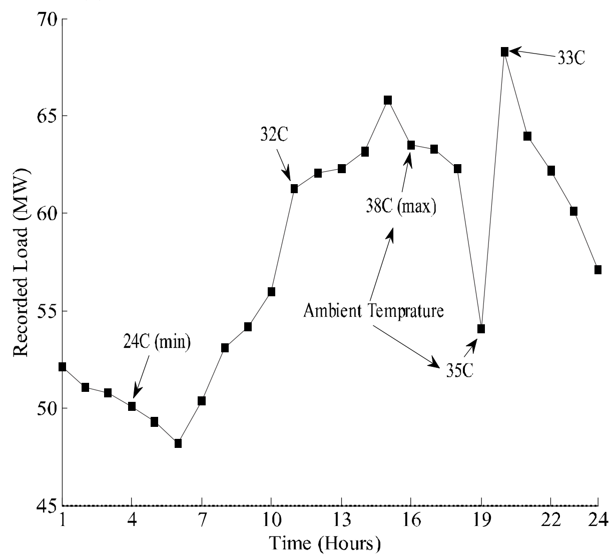


FIG. 1(d). 132KV QASIMABAD GRID-HESCO OCTOBER 01, 2012

FIG. 1. HOUR BY HOUR TEMPERATURE AND RECORDED LOAD OF 132KV QASIMABAD GRID STATION

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left[\left(ActualLoad_i - ForecastedLoad_i\right)\right]^2 \qquad (21)$$

Fig. 4(a-d) shows the least square load foresting error of the proposed algorithm for four selected days respectively for four different regression techniques.

It is clear from results that with least square approach, error is minimized greatly when load forecasting differences are in decimal values whereas the load forecasting error increases in squared manner when the difference between the actual and recorded is in real values. Table 1 illustrate the summary of Mean Square Load Forecasting Error with four different techniques for four selected days of 2012.

The summary shows that on 1st January 2012, Exponential Regression has minimum squared error whereas Linear Regression has maximum squared error. For 1st April 2012 Quadratic Regression has minimum and Multiple Linear Regression has maximum squared error. On 1st July 2012, Quadratic Regression has minimum while Exponential Regression has maximum squared error. Again for 1st October 2012, Quadratic Regression has minimum and Multiple Linear Regression has maximum squared error. The overall load forecasting error is 2.98% which is very much acceptable. From four regression techniques, Quadratic Regression technique performs better compared to than other techniques because being the nonlinear approach, Quadratic Regression techniques can optimally fit broad range of functions and data sets.

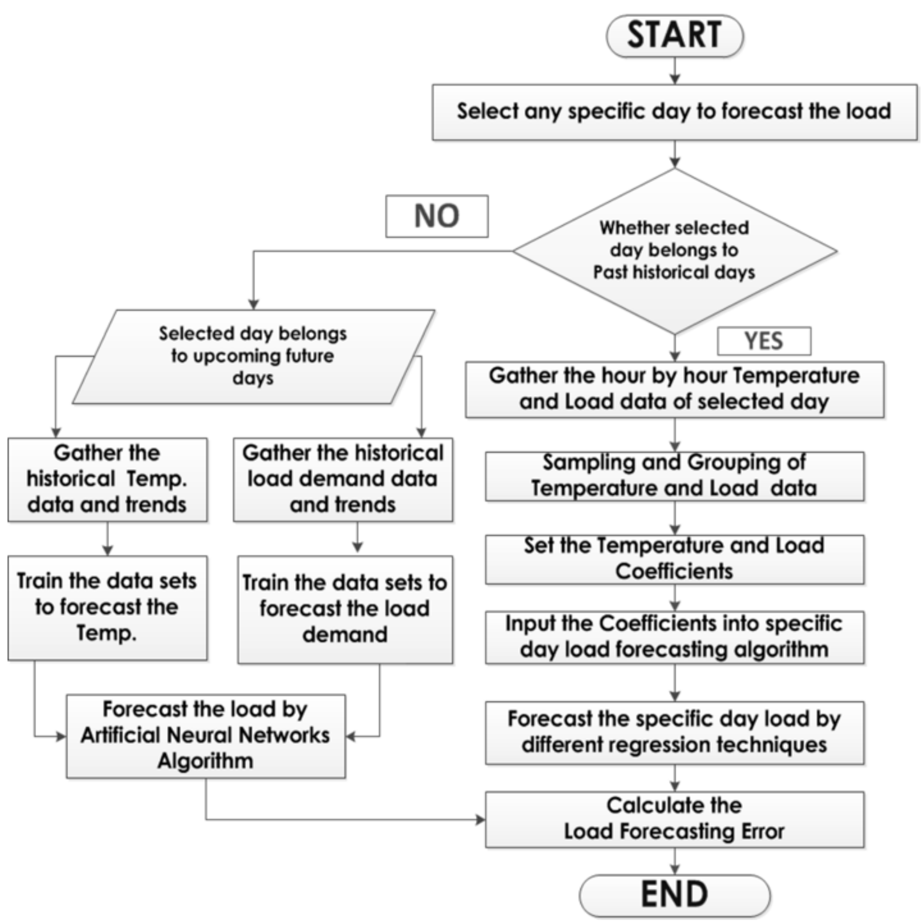


FIG. 2. SPECIFIC DAY HOUR BY HOUR LOAD FORECASTING ALGORITHM FLOWCHART

6. CONCLUSIONS

In the planning and management of power generation, transmission and distribution systems, load forecasting is the key factor. The load forecasting is a non-trivial task due to non-linear nature of load as load pattern of any specific time or day technically depends on different exogenous factors including whether variance or peak load demand which can greatly affect the load forecasting. To have more accurate load forecasting it is imperative to consider hour by hour temperature variance and load behavior. Therefore forecasting methods by considering linear and non-linear techniques will yield more realistic results.

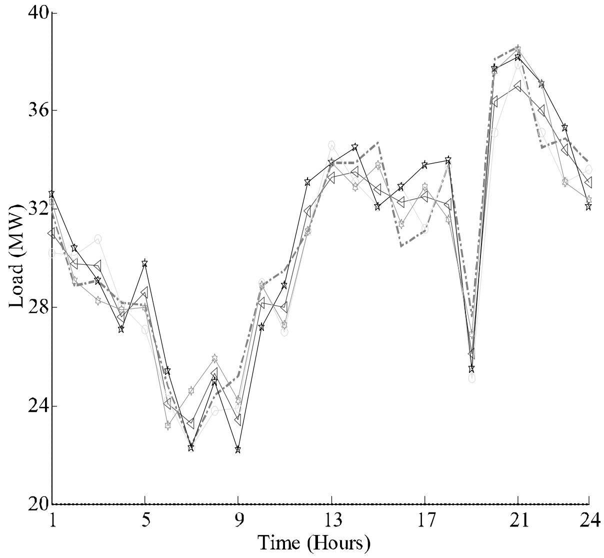


FIG. 3(a). 132 KV QASIMABAD GRID HESCO-LOAD FORECASTING JANUARY 01, 2012

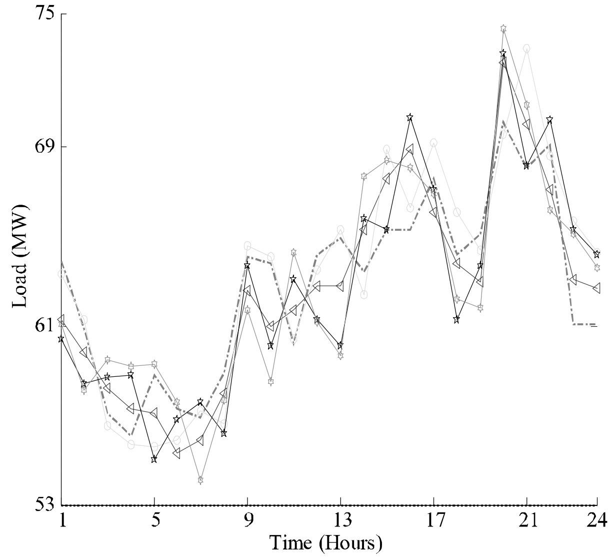
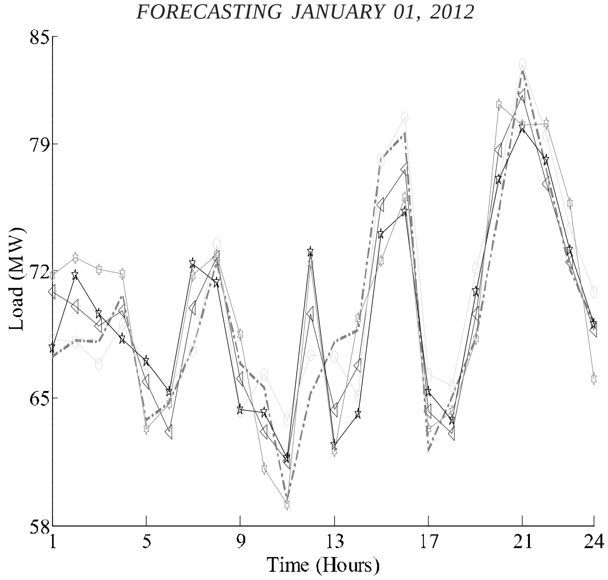


FIG. 3(b). 132 KV QASIMABAD GRID HESCO-LOAD FORECASTING APRIL 01, 2012



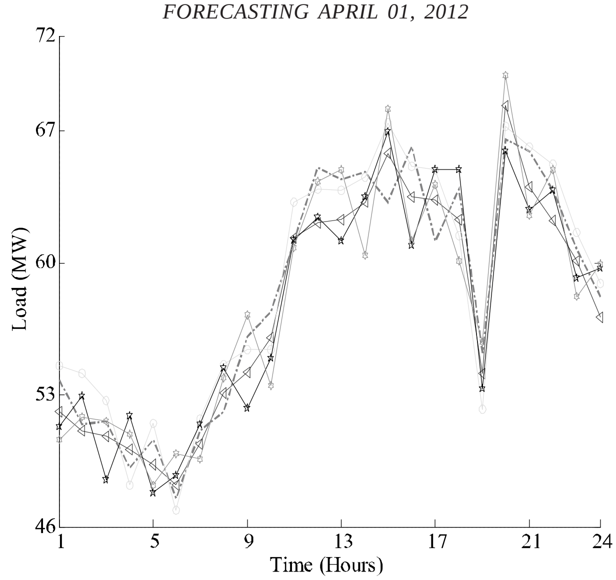


FIG. 3(c). 132 KV QASIMABAD GRID HESCO-LOAD FORECASTING JULY 01, 2012

FIG. 3(d). 132 KV QASIMABAD GRID HESCO-LOAD FORECASTING OCTOBER 01, 2012

FIG. 3. ACTUAL RECORDED VS. FORECASTED LOAD BY FOUR DIFFERENT REGRESSION TECHNIQUES

In this work two linear and two non-linear regressions load forecasting techniques are modeled by using least square error approach. For model validation 132kV grid station of HESCO is selected. To model the load, hour by hour temperature and load demand of four days was taking as input. In this study, when the different load forecasting techniques are compared, quadratic regression approach yields more accurate results because it can fit the broad range of data sets and functions.

As load is a complex pattern, any abnormal changes in the input parameters or unforeseen changes in demand results in load forecasting errors, the concept of adaptive artificial intelligent expert systems with supervised learning can

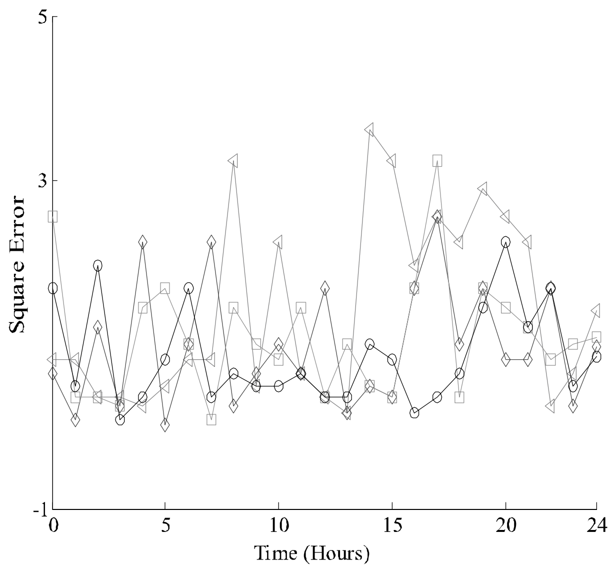


FIG. 4(a). 132KV QASIMQBAD GRID HESCO JANUARY 01, 2012

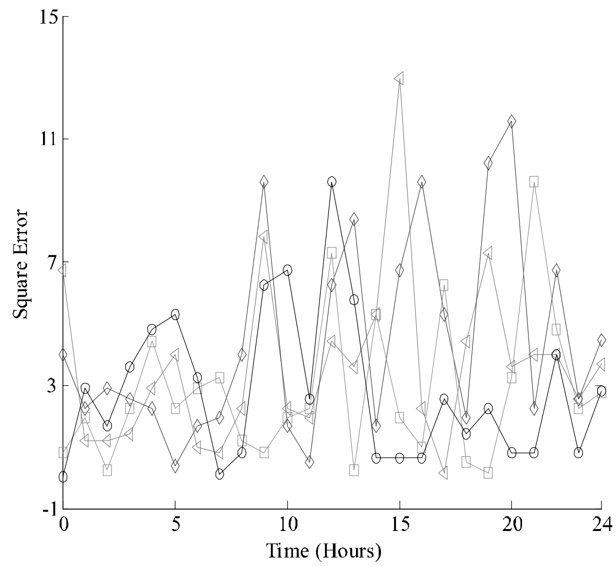
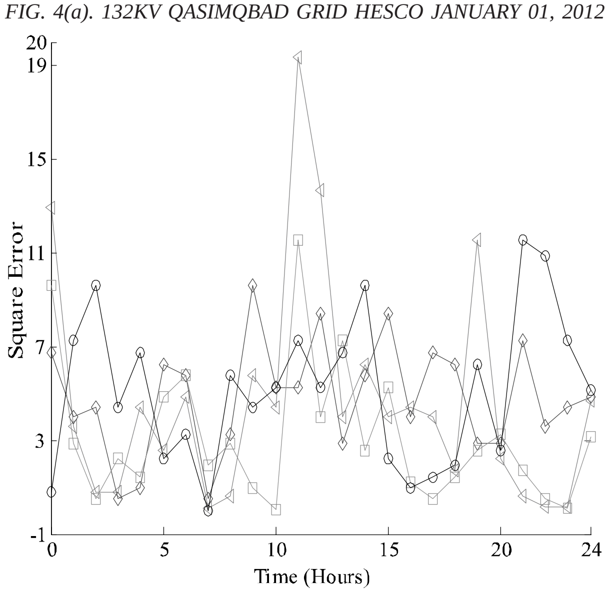


FIG. 4(b). 132KV QASIMQBAD GRID HESCO APRIL 01, 2012



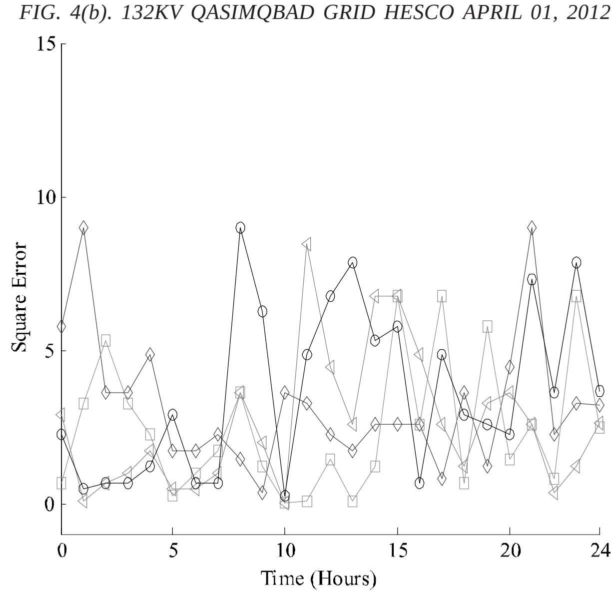


FIG. 4(c). 132KV QASIMQBAD GRID HESCO JULY 01, 2012

FIG. 4(d). 132KV QASIMQBAD GRID HESCO OCTOBER 01, 2012

FIG. 4(a-d). LOAD FORESTING ERROR OF THE PROPOSED ALGORITHM FOR FOUR SELECTED DAYS

TABLE 1. MEAN SQUARE LOAD FORECASTING ERROR OF PROPOSED MODEL

Day/ Technique	Linear Regression	Multiple Linear Regression	Quadratic Regression	Exponential Regression	MSE (Technique Wise)
January 01, 2012	1.41	0.97	1.08	0.85	1.07
April 01, 2012	3.67	4.46	2.78	2.83	3.43
July 01, 2012	4.71	4.84	3.12	5.16	4.45
October 01, 2012	2.59	3.21	2.47	3.63	2.97
MSE (Day wise)	3.09	3.37	2.36	3.11	2.98

overcome such type of irregularities. Very short term load forecasting models that may be few minutes to few hours are getting more popularity nowadays. In future, we will extend this work to more optimized results by adopting hour by hour real time temperature variations for very short term load forecasting using adaptive artificial intelligent expert systems.

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