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Short-term Load Forecasting using traditional demand forecasting

Indraraj B. Sindhav[1], Kaushik Khatua[2]
[1]*Electrical Department,Marwadi Education Foundation, Rajkot, India.*
[2]*Electrical Department,Marwadi Education Foundation, Rajkot, India.*

Abstract: *In electrical engineering load forecasting have been tried out using traditional forecasting models and artificial intelligence techniques and have become one of the major research fields. An accurate and efficient Short-term load forecasting (STLF) plays a vital role for economic operational planning of both regulated power systems and electricity markets. To develop a solution/methodology to demand forecast (Hourly load forecast) and by incorporating weather conditions. However, STLF it is pertinent to understand conventional methods. Therefore, popular conventional methods were implemented to learn methods for STLF. This paper presents Simple Moving Average, Weighted Moving Average, Exponential Moving Average, Auto Regressive and Multiple linear regressions for short term load forecasting. Conventional technique approach is implemented on historical load data for forecasting the load. PGVCL hourly load data used for training and testing is collected from ALDC, Jetpur, Gujarat. Hence hereby in this paper I have compared five conventional methods for STLF and have come out with a result that forecasting errors of time series models gives reasonably accurate hour ahead load forecast.*
Keywords: *Short-Term Load forecasting, traditional methods, matlab coding results.*

I. Introduction

The electrical load forecasting is useful in optimal dispatch of generation, power system security assessment, generation reserve allocation, market operation, etc. Although load forecasting had been an interest for many years, however, in deregulated Electricity Markets (EMs), Short-Term (one hour to a week ahead) Load Forecasting (STLF) especially has gained much more important and greater challenges than ever before, because of the variability and non-stationary in the electricity load time series. In the deregulated (competitive) framework, the precise STLF is an essential tool, not only for the Independent System Operator (ISO) but also for the market participants (e.g., Generating Companies (GenCos), Load Serving Entities (LSEs), retailers, etc.) who do the electricity trading in the Ems. [1]

Several different methods, techniques and algorithm have been developed to forecast load demands, with the focus on improving the prediction accuracy. The approach using time series analysis is among the main areas with rich research effort, with specially formulated methods for data in various contexts. Time series models are proposed, namely, the traditional techniques model. [2]

Different forecasting techniques have been applied to the problem of daily load forecast. Almost all of these techniques fall in the realm of statistical techniques.

In this paper a comparative evaluation of five Short-term load forecasting techniques is presented. These techniques are:

1. Simple Moving Average;
2. Weighted Moving Average;
3. Exponential Smoothing;
4. Auto Regressive; and
5. Multiple Linear regressions

The paper is organized as follows. Section II introduces the five above mentioned traditional method and explains how they would be used in analyzing and forecasting the load demand with a brief note on forecasting error measurement. Section III is the case study whereby Paschim Gujarat Vij Co. Ltd. Load demands are first plotted for visual comparison of hourly ahead data. Then models would be applied with forecasts generated and compared with the amounts actually demand. Section IV concludes the paper. [3]

II. Traditional Forecasting Techniques

1. Simple Moving Average

SMA is the most basic of the moving averages used for forecasting. A simple moving average (SMA) is formed by finding the average load of a currency or commodity over a set number of periods. Most often, the recent load is used to compute the moving average. A 5-day simple moving average is the five day sum of closing load divided by five. As its name implies, a moving average is an average that moves. Old data is dropped as new data comes available. [6]

$$MA_n = \sum_{i=1}^{n} Di / n$$

2. Weighted Moving Average (WMA)

This average is calculated by multiplying each of the previous day's data by weight. Therefore it is designed to put more weight on recent data and less weight on past data. In other words, it is simply a moving average that is weighted so that more recent values are more heavily weighted than values further in the past. Evidence also indicates that the use of this type of moving average gives better volatility estimates than the simple moving average. The formula of the WMA average is: [6]

$$WMA = \sum_{t=1}^{n} CiDi$$

Where Ci = Weights for Periods
Di = Demand for Periods

3. Exponential Moving Averages (EMA)

Exponential moving averages reduce the lag by applying more weight to recent loads. The weighting applied to the most recent loads depends on the number of periods in the moving average. An exponential moving average is similar to a simple moving average, but whereas a simple moving average removes the oldest loads as new prices become available, an exponential moving average calculates the average of all historical ranges, starting at the point you specify. [8]

$$F_{\mathrm{t}} = \alpha D_{t-1} + (1-\alpha) F_{t-1}$$

α = Smoothing Coefficient
Dt-1 = Actual demand for recent period
Ft-1 = demand forecast for recent period
Ft = Forecast of next period demand

4. Auto Regressive (AR)

In the AR process, the current value of the time series y(t) is expressed linearly in terms of its previous values y(t-1), y(t-2)…..) and a random noise a(t). The order of this process depends on the oldest previous value at which y(t) is regressed on.

$$y(t) = \Phi_1 y(t-1) + \Phi_2 y(t-2) + \ldots\ldots\ldots\ldots\ldots \Phi_P y(t-\mathrm{P}) + a(t)$$

5. Multiple Linear Regression (MLR)

In the multiple linear regression (MLR) method, the load is found in terms of explanatory variables such as weather and non-weather variables which influence the electrical load. The load model using this method is expressed in the form as.

$y(t) = a_o + a_1X_1(t) + \ldots\ldots\ldots + a_nX_n(t) + a(t)$

y(t) = electrical load
$X_1(t) + \ldots\ldots X_n(t)$ = explanatory variables correlated with y(t)
a(t) = a random variable with zero mean and constant variance
$a_o, a_1 \ldots\ldots a_{n\,=}$ regression coefficients

The explanatory variables of this model are identified on the basis of correlation analysis on each of these (independent) variables with the load (dependent) variable. Experience about the load to be modeled helps an initial identification of the suspected influential variables. The estimation of the regression coefficients is usually found using the least square estimation technique. Statistical tests significance of these regression coefficients. The t-ratios resulting from these tests determine the significance of each of these coefficients and correspondingly the significance of the associated variables with these coefficients.

III. Case Study

To demonstrate the effectiveness of the Time Series model for the application of STLF, hour-ahead load forecasting in PGVCL EM is considered in this paper. In EMs, one-hour a head load forecast is often useful for real-time operation. In this methods data sets used for training and testing of the time series model for hour-ahead load forecasting. Then structure of SMA, WMA and ES model is presented based on a two-step procedure followed by load forecasting simulation results for test weekday.

1. Hour Ahead Load Forecasting Results

The performance of a load forecasting system based on this time series forecasting methodology is demonstrated using data from PGVCL-Rajkot for different day types is used for training and load forecasting. Real time data that includes historical hourly load demand over a week is collected from Paschim Gujarat Vij Co. Ltd. In this paper simple moving average, weighted moving average and exponential smoothing method are used. The forecasted load is compared with the actual load and average percentage error is calculated. In this paper hourly-ahead forecast is in this paper. Described as below.

$$MAPE\,(\%) = \frac{1}{N}\sum_{1}^{n}\frac{|load\ actual - load\ forecast|}{load\ actual}\ X\ 100$$

Where, $L^{act}h$ and $L^{for}h$ is the actual and forecasted load of hour h , respectively; and N is the number of hours.
Selected day – 31st May, Sat

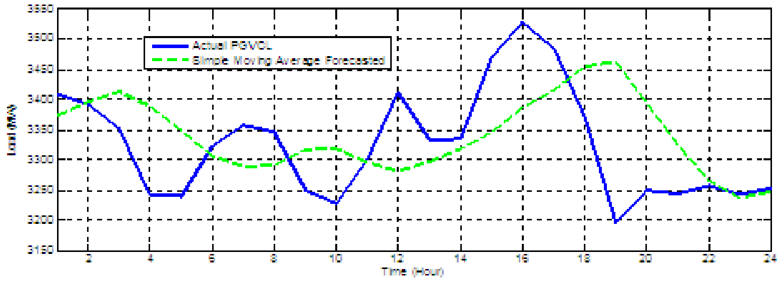

Fig. 1 Actual and forecasted load for selected weekday of SMA

Time (Hrs.)	Actual Load (MW)	Forecasted Load (MW)	APE
1	3408.92	3322.11	2.55
2	3391.43	3373.78	0.52
3	3351.45	3395.46	-1.31
4	3242.07	3412.69	-5.26
5	3240.31	3389.22	-4.6
6	3322.74	3348.47	-0.77
7	3357.85	3306.31	1.53
8	3346.42	3289.14	1.71
9	3249.08	3290.74	-1.28
10	3227.99	3316.83	-2.75
11	3300.79	3319.02	-0.55
12	3411.38	3295.34	3.4
13	3333.45	3281.07	1.57
14	3334.84	3297.31	1.13
15	3469.42	3318.4	4.35
16	3528.35	3345.12	5.19
17	3483.58	3387.27	2.76
18	3370.38	3416.51	-1.37
19	3195.48	3454.05	-8.09
20	3248.76	3462.93	-6.59
21	3244.47	3394.45	-4.62
22	3258	3324.55	-2.04
23	3242.42	3264.77	-0.69
24	3253.49	3236.68	0.52

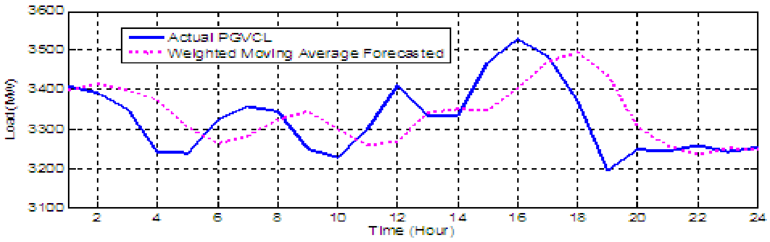

Fig.2 Actual and forecasted load for selected weekday of WMA

Time (Hrs.)	Actual Load (MW)	Forecasted Load (MW)	APE
1	3408.92	3400.64	0.24
2	3391.43	3415.05	-0.7
3	3351.45	3399.41	-1.43
4	3242.07	3374.94	-4.1
5	3240.31	3304.75	-1.99
6	3322.74	3263.07	1.8
7	3357.85	3281.87	2.26
8	3346.42	3323.81	0.68
9	3249.08	3345.11	-2.96
10	3227.99	3300.04	-2.23
11	3300.79	3258.01	1.3
12	3411.38	3268.61	4.19
13	3333.45	3341.53	-0.24
14	3334.84	3350.3	-0.46
15	3469.42	3349.73	3.45
16	3528.35	3401.85	3.59
17	3483.58	3471.97	0.33
18	3370.38	3494.18	-3.67
19	3195.48	3435.94	-7.52
20	3248.76	3305.57	-1.75
21	3244.47	3257.1	-0.39
22	3258	3235.96	0.68
23	3242.42	3252.09	-0.3
24	3253.49	3247.5	0.18

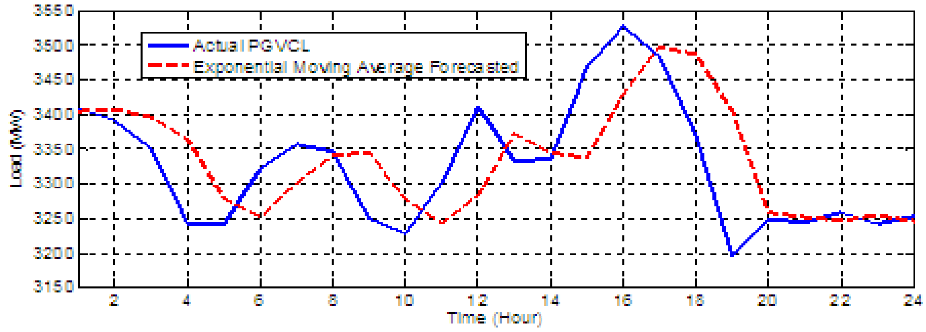

Fig. 3 Actual and forecasted load for selected weekday of EMA

Time (Hrs.)	Actual Load (MW)	Forecasted Load (MW)	APE
1	3408.92	3405.1	0.11
2	3391.43	3407.78	-0.48
3	3351.45	3396.33	-1.34
4	3242.07	3364.92	-3.79
5	3240.31	3278.92	-1.19
6	3322.74	3251.89	2.13
7	3357.85	3301.48	1.68
8	3346.42	3340.94	0.16
9	3249.08	3344.78	-2.95
10	3227.99	3277.79	-1.54
11	3300.79	3242.93	1.75
12	3411.38	3283.44	3.75
13	3333.45	3373	-1.19
14	3334.84	3345.31	-0.31
15	3469.42	3337.98	3.79
16	3528.35	3429.99	2.79
17	3483.58	3498.84	-0.44
18	3370.38	3488.16	-3.49
19	3195.48	3405.72	-6.58
20	3248.76	3258.55	-0.3
21	3244.47	3251.7	-0.22
22	3258	3246.64	0.35
23	3242.42	3254.59	-0.38
24	3253.49	3246.07	0.23

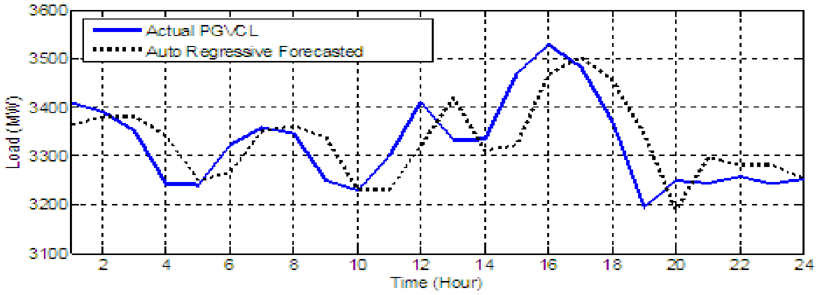

Fig. 4.4 Actual and forecasted load for selected weekday of AR

Time (Hrs.)	Actual Load (MW)	Forecasted Load (MW)	APE
1	3408.92	3363.26	1.33
2	3391.43	3380.03	0.33
3	3351.45	3382.37	-0.92
4	3242.07	3340.94	-3.04
5	3240.31	3248.45	-0.25
6	3322.74	3265.85	1.71
7	3357.85	3351.46	0.18
8	3346.42	3361.08	-0.43
9	3249.08	3336.89	-2.7
10	3227.99	3229.72	-0.05
11	3300.79	3231.21	2.1
12	3411.38	3321.33	2.63
13	3333.45	3419.42	-2.57
14	3334.84	3309.68	0.75
15	3469.42	3322.67	4.22
16	3528.35	3469.18	1.67
17	3483.58	3503.5	-0.57
18	3370.38	3455.33	-2.52
19	3195.48	3345.76	-4.7
20	3248.76	3189.93	1.81
21	3244.47	3297.84	-1.64
22	3258	3280.91	-0.7
23	3242.42	3280.39	-1.17
24	3253.49	3252.55	0.02

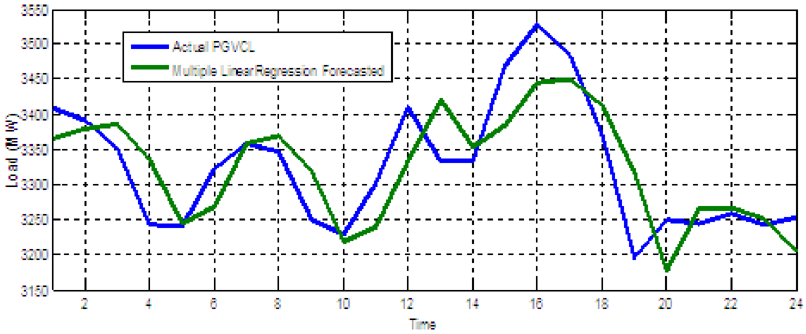

Fig. 4.5 Actual and forecasted load for selected weekday of MLR

Time (Hrs.)	Actual Load (MW)	Forecasted Load (MW)	APE
1	3408.92	3363.26	1.33
2	3391.43	3380.03	0.33
3	3351.45	3382.37	-0.92
4	3242.07	3340.94	-3.04
5	3240.31	3248.45	-0.25
6	3322.74	3265.85	1.71
7	3357.85	3351.46	0.18
8	3346.42	3361.08	-0.43
9	3249.08	3336.89	-2.7
10	3227.99	3229.72	-0.05
11	3300.79	3231.21	2.1
12	3411.38	3321.33	2.63
13	3333.45	3419.42	-2.57
14	3334.84	3309.68	0.75
15	3469.42	3322.67	4.22
16	3528.35	3469.18	1.67
17	3483.58	3503.5	-0.57
18	3370.38	3455.33	-2.52
19	3195.48	3345.76	-4.7
20	3248.76	3189.93	1.81
21	3244.47	3297.84	-1.64
22	3258	3280.91	-0.7
23	3242.42	3280.39	-1.17
24	3253.49	3252.55	0.02

Forecast Models	Hourly load forecast MAPE(%)
Simple Moving Average	2.5
Weighted Moving Average	2.52
Exponential Moving Average	2.54
Auto Regressive	1.59
Multiple Linear Regression	**1.39**

Important Features	Conventional Methods				
	SMA	WMA	EMA	AR	MLR
Load Information	Cosidered	Cosidered	Cosidered	Cosidered	Cosidered
Weather Information	Ignored	Ignored	Ignored	Ignored	Cosidered
Functional relationship between load and weather variables	Ignored	Ignored	Ignored	Ignored	Cosidered
Complex mathematical calculations	Required	Required	Required	Required	Required
Time required for prediction	More	More	More	More	More
Adaptability	Less	Less	Less	Less	Less

IV. Conclusion

This paper is based on the comparative analysis of five Conventional Short term load forecasting techniques. During the implementation of these techniques certain interesting properties of the load and the variables have been observed. One-hour-ahead load forecast is often useful for real-time operation of both regulated power systems and Electricity Markets (EMs). In this paper, time series forecasting traditional techniques i.e. simple moving average, weighted moving average, auto regressive, multiple linear regression and exponential smoothing. time series forecasting traditional techniques is applied for hour-ahead load forecasting in PGVCL electricity market. Two test days corresponding to one month demand data are considered to validate the application of time series for load forecasting. The presented results reveal that TSP based forecast gives reasonably accurate hour-ahead load forecasts.

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