International Journal of u- and e- Service, Science and Technology
Vol.9, No. 8 (2016), pp.179-188
http://dx.doi.org/10.14257/ijunesst.2016.9.8.15

Long-Term Minute-Wise Wind Forecasting using Time Series Modelling

Harish Krishnappa

Intern
State load Dispatch Centre,Karnataka, India
harish.31k@gmail.com

Abstract

With innovations in technology, alternate energies like solar and wind are becoming more popular. Utilities in some parts of the world rely on Wind energy over coal or gas fired power. Wind energy output is highly mercurial in nature, it changes rapidly even within the course of minutes. Hence, power system operators have to predict changes of the wind power production in order to schedule the Spinning reserve capacity and to manage the grid operations. To reduce the reserve capacity and increase the wind power penetration, the accurate forecasting of wind speed is needed. In addition, wind power forecasting plays an important role in the allocation of balancing power. Although the prediction accuracy of wind power forecasting is lower than the prediction accuracy of load forecasting, wind power forecasts still play a key role to address the operation challenges in electricity supply. This paper deals with Long-term forecast of wind energy for the state grid of Karnataka by employing a simple time series multiplicative modelling. Wind energy production is predicted for the year 2015 using the data collected from 2011-2014.

Keywords: *Classical Multiplicative model, Linear Regression, Mean Error (ME), Mean Absolute Error (MAE), Mean Absolute Percentage error (MAPE), Mean square error (MSE), Seasonality, Trend*

1. Introduction

Energy forecasting has become vital to alternate energy generation as there are no models for the underlying natural processes in alternate energy generations. Forecasting deals with making an assessment of the future, with a knowledge of present and the past. This paper makes use of time series data, where the prediction of the future value is solely based on past values. The pattern of historical data series is simply captured and extrapolated into the future. Due to the random behavior of wind power productions, the output predictions of the productions are really helpful to increase the efficiency of wind power [1-2]. Because “capacity reserve” of a certain amount of electricity will be needed to compensate for the fluctuation if there are some unbalance between the electricity production and consumption. But the capacity reserves raise the economic and environment cost of electricity production because most capacity reserves are generated by conventional power plant [3]. Therefore, the predictions which are delivered to the Power System Operators to suggest the electricity system’s adjustment for the reserves can reduce the cost of the short-term capacity reservations and hence make wind power more valuable. The predictions could also be used for other relevant purposes such as generation and transmission maintenance planning, economic dispatch, energy storage optimization and energy trading [4-7]. Various methods classified according to time-scales or methodology like Ultra-short-term forecasting, which is from few minutes to 1 hour ahead, Short-term forecasting, which is from 1 hour to several hours ahead, Medium-term forecasting, which is from several hours to 1 week ahead and Long-term

ISSN: 2005-4246 IJUNESST
Copyright ⓒ 2016 SERSC

forecasting, which is from 1 week to 1 year or more ahead are available for wind forecasting. Minute-wise wind data collected of the state pool for three years from 2011-13 is as shown in Figure 1. This paper deals with Long-term forecasting which plays an important role in maintenance planning and operational management.

2. Understanding the Data

Time series data reveals trends over time, regular seasonal behavior and random patterns in the data [8]. There are three types of time series patterns as shown in Figure 2.

2.1. Trend Pattern (T_t)

A trend exists when there is a long-term increase or decrease in the data. For example, power demand increases every year. It does not have to be linear

2.2. Seasonal Pattern (S_t)

When the pattern is dependent on the season (e.g., the quarter of the year, the month, or day of the week). Seasonality is always of a fixed and known period.

2.3. Cyclic Pattern

A cyclic pattern exists when data exhibit rises and falls that are not of fixed period.

Wind power typically contains both a seasonal and trend component. If E_t is the random component in the data and Y_t is the actual data at time t, then a multiplicative decomposition is given by

$$Y_t = S_t * T_t * E_t \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (2.1)$$

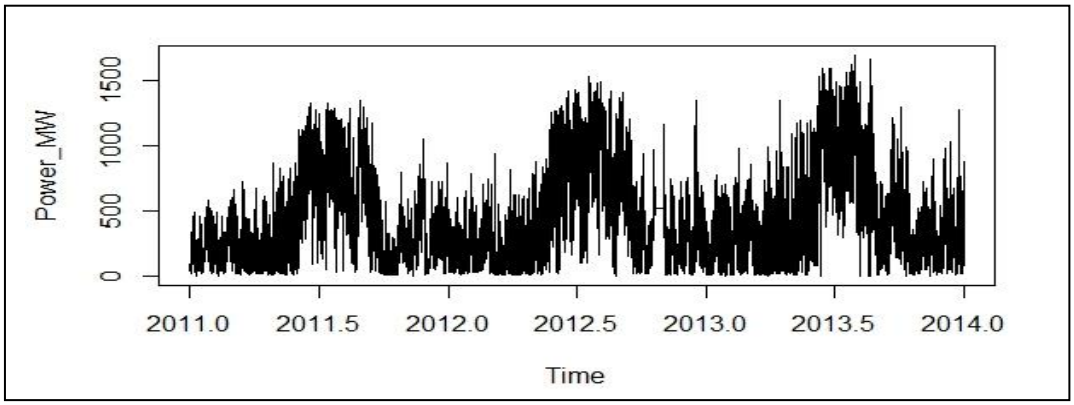

Figure 1. Minute-Wise Wind Power of the State Pool of Karnataka from 2011-13

3. Forecasting Minute-Wise Data

The first step in a classical decomposition is to use a moving average method to estimate the trend-cycle. One way of modifying the influence of all past data is to specify how many past values will be included in the mean, which depicts an idea that future values will be affected only by recent past [8-12].

$$F_{t+1} = (1/k)*\sum_{(i=t-k+1)}^{t} Y_i \quad \ldots\ldots\ldots\ldots\ldots \quad (3.1)$$

It is called Moving average of order k, MA (k). Since, the paper deals with forecasting for each month separately, k is the period of that respective month as shown in Table 1.

 Copyright ⓒ 2016 SERSC

Moving average eliminates some of the randomness in the data, leaving a smooth trend-cycle component. Period (k) is calculated w.r.t minutes in a month as it is a minute-wise forecast. For example, for January it is 60*24*31 (minutes*hours*days) = 44640. Similarly, for February it is 40320 for non – leap years.

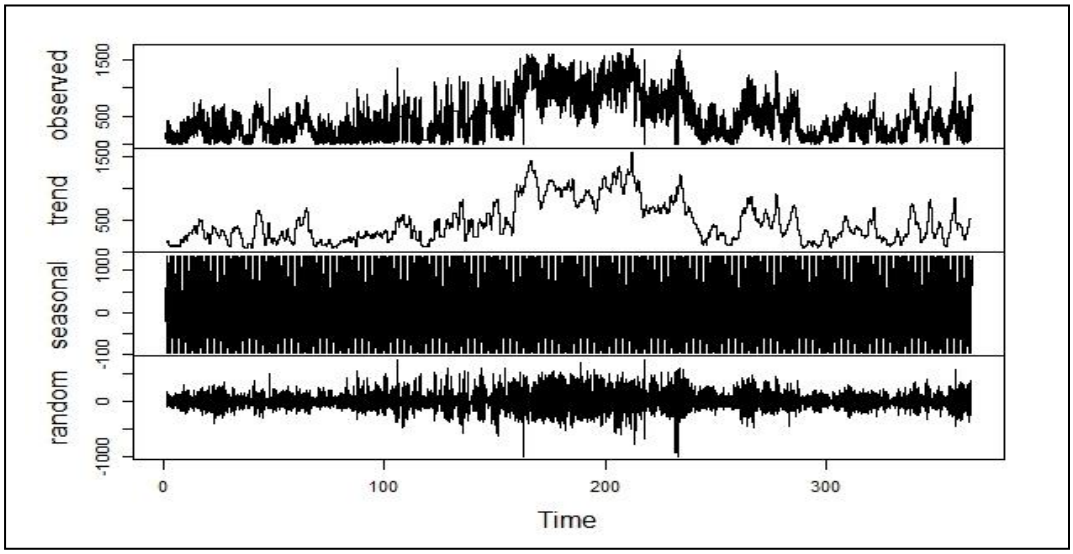

Figure 2. Decomposed Time Series Wind Data of the Year, 2013

Table 1. K Considered for Each Month

MONTH	PERIOD (k)
January	44640
February	40320
March	44640
April	43200
May	44640
June	43200
July	44640
August	44640
September	43200
October	44640
November	43200
December	44640

The next step is making the results symmetric by making use of "centred moving average (CMA)" of order 44640, which takes the average of two consecutive MA.

$$CMA_t = (1/2)*(MA_t + MA_{t+1}) \ldots\ldots\ldots \quad (3.2)$$

After finding the CMA or baseline for the data, we can find the seasonal and random component (S_t,E_t), which is given by

$$S_t,E_t = Y_t / CMA_t \ldots\ldots\ldots\ldots \quad \ldots\ldots\ldots \quad (3.3)$$

Extraction of the seasonal and random component of the data is shown in Figure 4, extraction of only seasonal component is as shown in Figure 5.

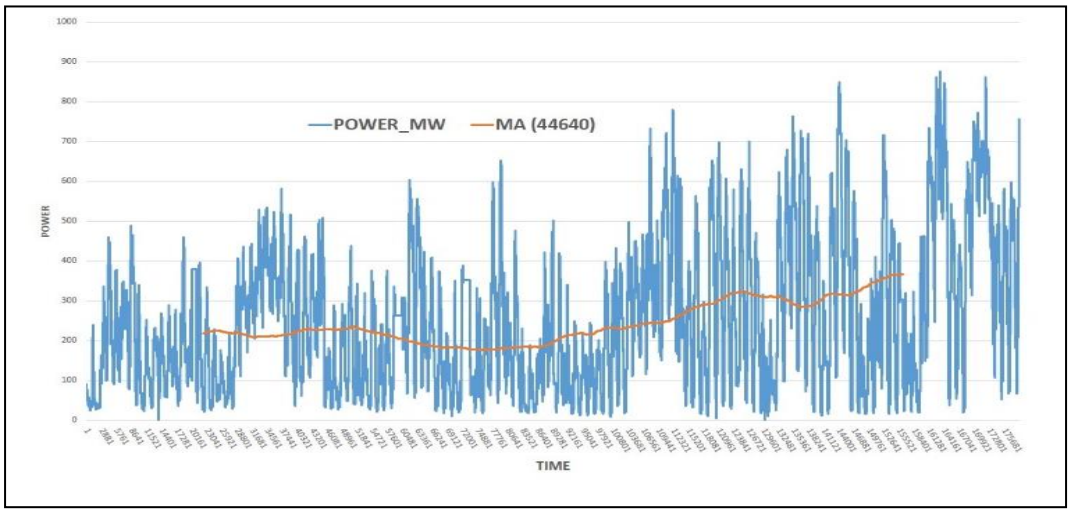

Figure 3. January Forecast Showing Actual Wind Data and Moving Average

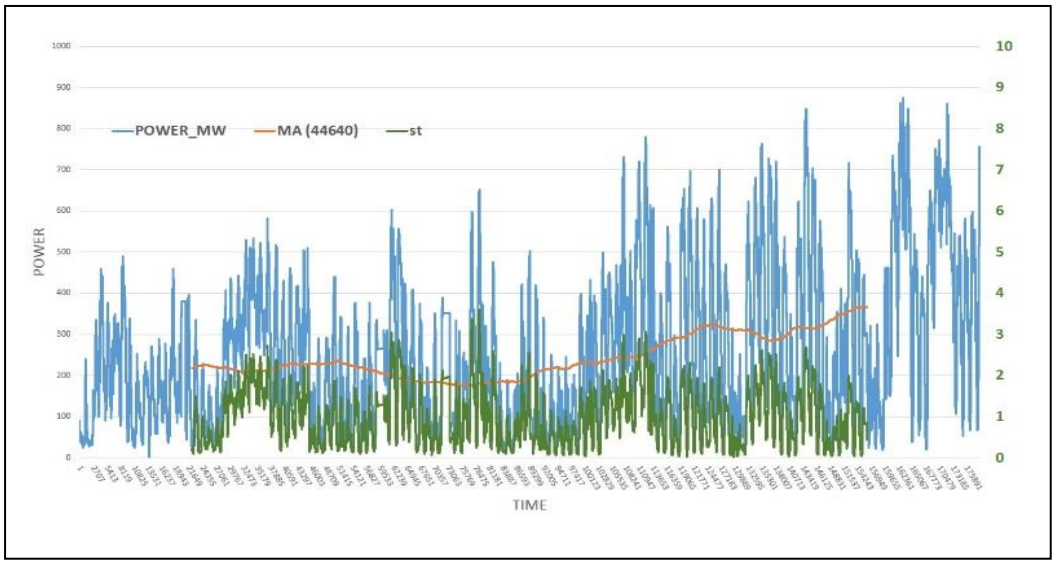

Figure 4. January Forecast with Seasonal and Irregular Components Shown in Green

Next step is to de-seasonalize the data in order to further smoothen the data for forecasting as shown in Figure 6. Using de-seasonalized components as y variables in simple linear regression, we find the trend component. Simple regression refers to any mapping of single variable y, which is the forecast variable, on a single variable x, which is independent. Simple linear regression is used for three main purposes like describing the linear dependence of one variable on another, to predict values of one variable from values of another, for which more data is available and to correct for the linear dependence of one variable on another, in order to clarify other features of its variability. However, in excel one can use the DATA ANALYSIS add – in to get the output in a single step. The output obtained for the month of January is as shown in Figure 7.

 Copyright ⓒ 2016 SERSC

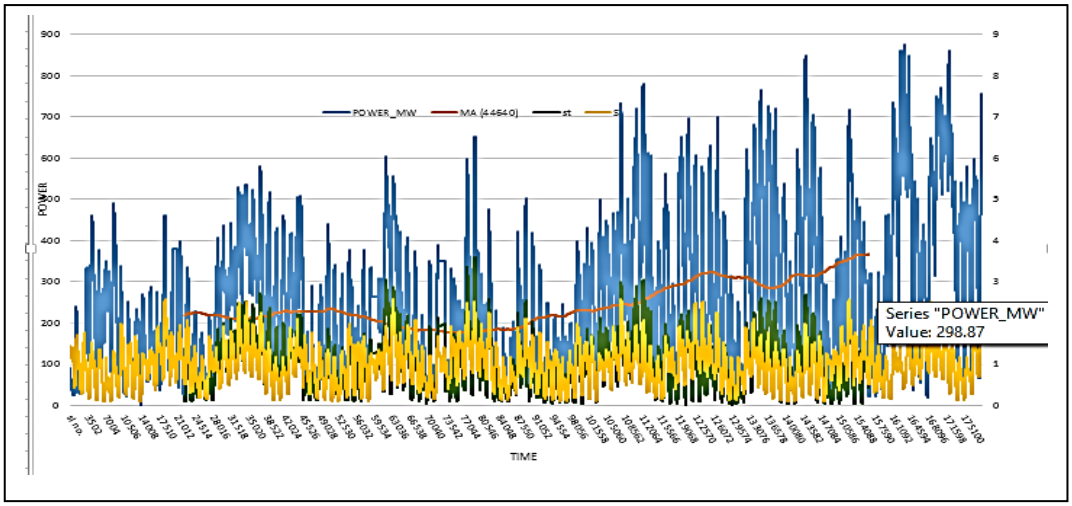

Figure 5. January Forecast with only Seasonal Components Shown in Yellow

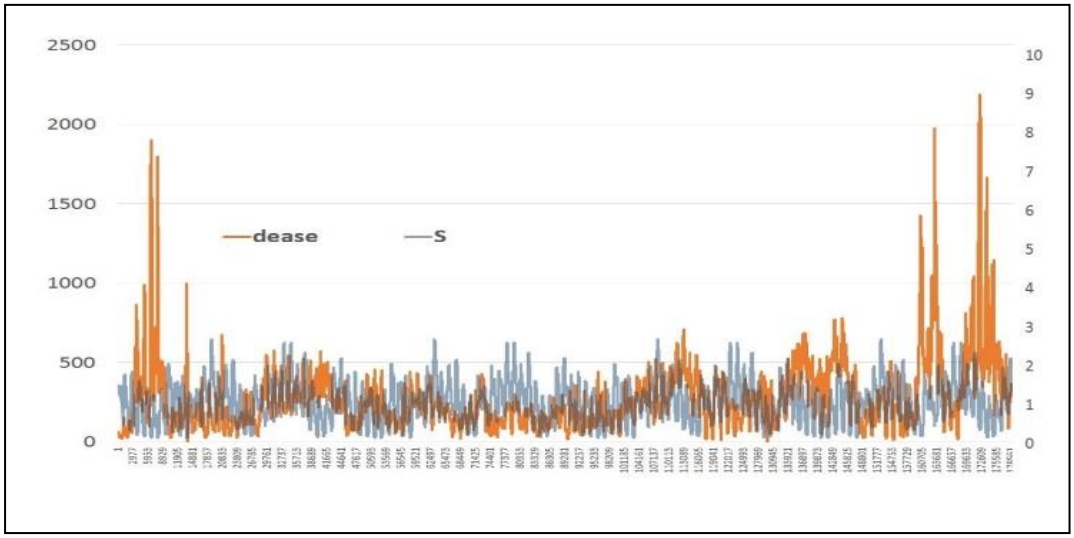

Figure 6. January Forecast with De- Seasonal Components Shown in Orange

Trend component is calculated by making use of the regression output using the formula,

T_t = Intercept + Slope * time $code_t$ …… (3.4)

For example for the month of January, Intercept and slope are 172.673 and 0.00111 respectively as shown in Figure 7 and for the first value considered time code is 1, for 525th value time code is 525 and so on. Trend line is shown in Figure 8. Finally, the forecasted value is given by,

$FORECAST_t = S_t * T_t$ …… (3.5)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.27984
R Square	0.07831
Adjusted R	0.0783
Standard E	196.794
Observatio	178560

ANOVA

	df	SS	MS	F	gnificance F
Regressior	1	5.9E+08	5.9E+08	15170.6	0
Residual	178558	6.9E+09	38728		
Total	178559	7.5E+09			

	Coefficients	andard Err	t Stat	P-value	Lower 95%	Upper 95%	ower 95.0%	pper 95.0%
Intercept	172.673	0.93143	185.384	0	170.847	174.499	170.847	174.499
sl no.	0.00111	9E-06	123.169	0	0.0011	0.00113	0.0011	0.00113

Figure 7. Output Obtained for Simple Linear Regression

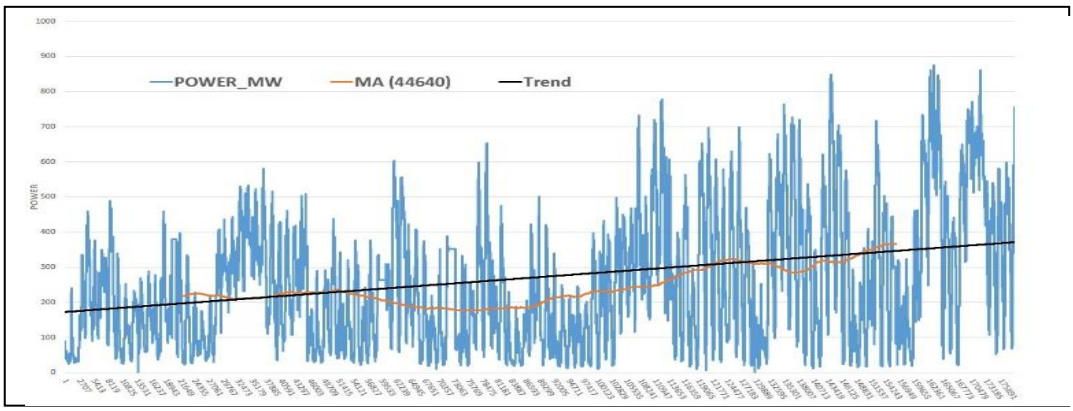

Figure 8. Trend Obtained for the Month of January

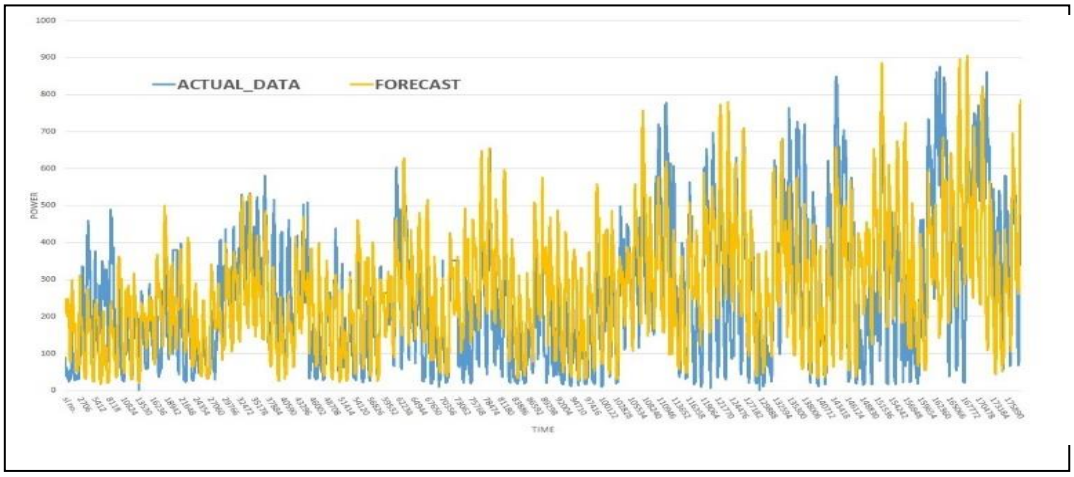

Figure 9. Minute-Wise Forecast Vs Actual Data for the Month of January

The obtained forecast value is plotted against the actual value as shown in Figure 9. These values can be extended to the future by a simple drag in excel worksheet to obtain the future forecast as shown in Figure 10.

 Copyright ⓒ 2016 SERSC

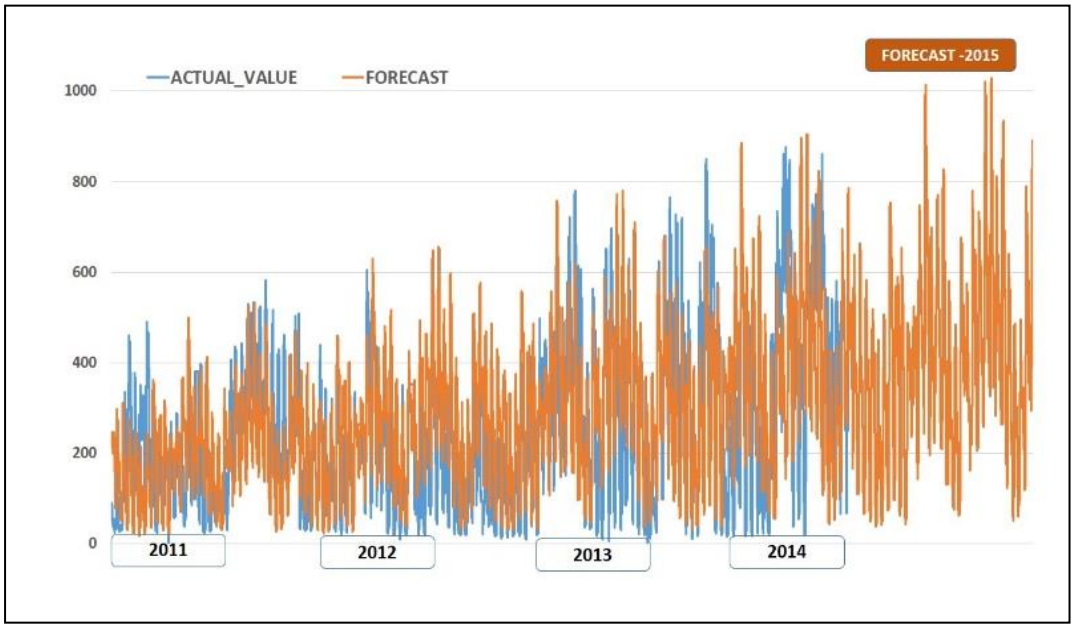

Figure 10. Minute- Wise Forecast for January – 2015

4. Forecast Accuracy

Accuracy is the major criterion for selecting a particular forecasting model. If F_t is the forecast value and Y_t is the actual value for period t, the error is given by,

$$e_t = Y_t - F_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \tag{4.1}$$

Mean error (ME) is given by,

$$ME = (e_1+e_2+\ldots\ldots+e_n)\ /n \quad \ldots\ldots \tag{4.2}$$

Mean absolute error (MAE) is given by,

$$MAE = (|e_1|+|e_2|+\ldots\ldots+|e_n|)\ /n \quad .. \tag{4.3}$$

Mean squared error (MSE) is given by,

$$MSE = ((e_1)^2 + (e_2)^2 +\ldots\ldots+ (e_n)^2)\ /\ n \quad .. \tag{4.4}$$

Percentage error (PE) is given by,

$$PE_t = (e_t\ /Y_t) * 100\% \ \ldots\ \ldots\ \ldots\ldots\ldots\ldots \tag{4.5}$$

Mean absolute percentage error (MAPE) is given by,

$$MAPE =(|PE_1| +|PE_2|+ \quad \ldots \quad .+ |PE_n|)\ /n \tag{4.6}$$

These errors quantify the accuracy of the forecast model. The mean error doesn't signify much, as the negative terms cancel out the positive terms. So, MAE gives a better measure. MAPE is the most commonly used error to measure the accuracy of the forecast model [12-14].

Table 2. Forecast Accuracy Measurements

Month	ME	MAE	MAPE	MSE
January	-18.3	110.0	65	19997.6
February	-47.1	116.3	50	23280.2
March	0.4	105.0	43	18925.1
April	-17.5	97.5	70	18265.3
May	-11.6	156.1	52	38696.6
June	-28.9	185.8	42	59074.5
July	-7.8	180.7	31	56051.9
August	-1.8	202.5	56	69576.7
September	-1.6	212.2	43	71156.0
October	-14.7	146.4	62	34657.8
November	-18.4	143.0	58	32087.3
December	-19.1	116.4	44	27810.5

Minute-wise forecasting has its own disadvantages when compared to hourly or daily forecasts. Accuracy of the forecast is highly questionable sometimes [15]. Classical multiplicative model is used for forecasting in this paper. Forecasts show what is likely to happen "on average", it is rarely perfect. So it is a good practice to complement forecasts with measures of the forecast uncertainty [16]. Errors have been tabulated for each month as shown in Table 2. The model was tested in real time at the SCADA centre from 8th to 10th December 2014 and the plot of actual data Vs Forecast data is as shown in Figure 11.

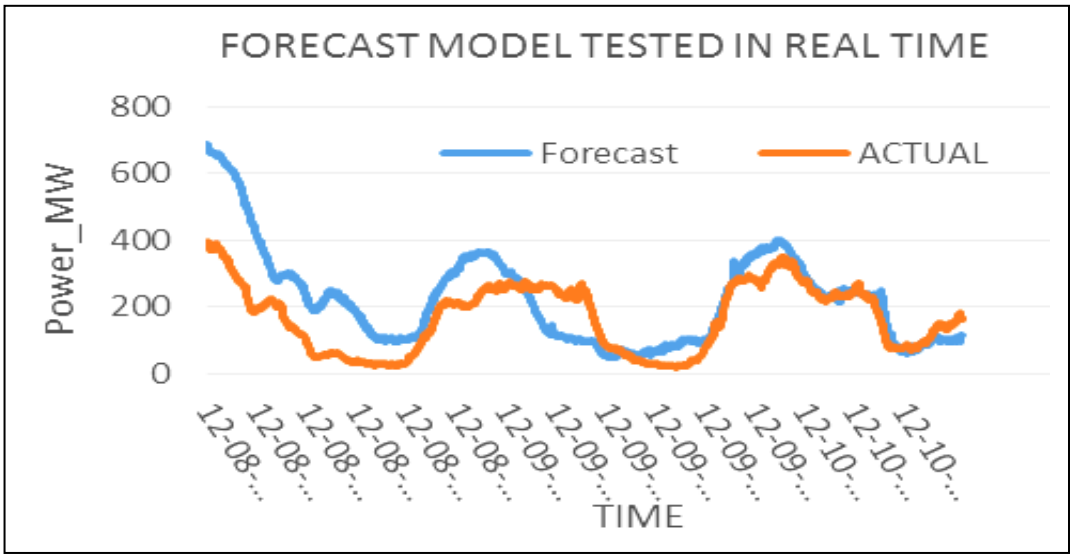

Figure 11. Minute-Wise Forecast Model Tested with Real Time Data from 08 to 10 December 2014

5. Conclusion

Minute-wise forecast was performed using the classical multiplicative model considering each month separately. Considering the data collected from 2011 to 2014, the forecast was performed for the year 2015. This paper clearly explains the

 Copyright ⓒ 2016 SERSC

steps involved in minute-wise forecasting. Platforms like R, MATLAB and Excel were used to analyze the data and carry out the forecast. Accuracy is dealt with in brief and errors are tabulated. This model was tested in real time at the SCADA center and the forecast data had the same trend has the actual wind data. Hence, the classical multiplicative forecast model is tested successfully and minute-wise data forecast is obtained.

Acknowledgment

Author owes an intellectual debt to the reference materials, which helped achieve sound knowledge about the topic and it would also make an excellent compilation for further reading on the topic. Author would like to thank Mr. Chandrashekharaiah S.B, Executive Engineer (SCADA Design), SLDC, Karnataka for his guidance on conducting this study. The encouragement by SLDC management and Staff is gratefully acknowledged.

References

[1] C. Kamath and Y. J. Fan, "Using Data Mining to Enable Integration of Wind Resources on the Power Grid", Statistical Analysis and Data Mining, vol. 5, no. 5, October **(2012)**, pp. 410-427.
[2] M. Milligan, M. Schwartz and Y. H. Wan "Statistical wind power forecasting models: Results for U.S. wind farms", National Conference on Wind Power, **(2003)** May18-21.
[3] M. A. Farahat, "Long – Term Industrial Load Forecasting and Planning Using Neural Networks Technique and Fuzzy Inference Method", 39th International Universities Power Engineering Conference UPEC'2004, University of West of England, Bristol, vol. 1, pp. 368-372, **(2004)** September 6-8.
[4] H. Mao, X. Zeng, G. Leng, Y. Zhai, and J. A. Keane, "Short-Term and Midterm Load Forecasting Using a Bi-level Optimization Model", IEEE Transactions on Power Systems, vol. 24, no. 2 **(2009)**, pp. 1080-1090.
[5] H. K. Alfares and M. Nazeeruddin,"Electric Load Forecasting: literature survey & classification of methods", International Journal of Systems Science, vol. 33, no. 1 **(2002)**, pp. 23-34.
[6] Q. Ding, "Long-Term Load Forecast Using Decision Tree Method", Power Systems Conference and Exposition, PSCE 06, IEEE PES, vol. 1, **(2006)**, pp.1541-1543.
[7] H. K. Alfares and M. Nazeeruddin, "Regression-Based Methodology for Daily Peak Load Forecasting," Proceedings of the 2nd International Conference on Operations and Quantitative Management, Ahmedabad, India, vol. 3-6, **(1999)**, pp. 468-471.
[8] K. U. Rao, "Power System Operation and Control", Wiley India, **(2013)**.
[9] B. L. B. Man, R. T. O"Connell and A. B. Koehler, "Forecasting, Time Series, and Regression: An Applied Approach," 4th ed. California: Thomas Brooks/ Cole, **(2005)**.
[10] L. Ghods and M. Kalantar, "Methods for long- term electric load demand forecasting; A comprehensive investigation", IEEE International Conference on Industrial Technology, Chengdu, **(2008)**, pp. 855-858.
[11] J. W. Taylor, "Triple seasonal methods for short-term electricity demand forecasting", European Journal of Operational Research, vol. 204, no. 1 **(2010)**, pp. 139 -152.
[12] A. M. Foley, "Current methods and advances in forecasting of wind power generation", Renewable Energy, vol. 37, no. 1, **(2012)**, pp. 1-8.
[13] G. Sideratos and N. D. Hatziargyriou, "An advanced statistical method for wind power forecasting", IEEE Transactions on Power Systems, vol. 22, no. 1, **(2012)** February, pp. 258-265.
[14] K. Rohrig and B. Lange "Application of wind power prediction tools for power system operations." IEEE Power Engineering Society, pp. 18-22, **(2006)** June.
[15] S. Rajagopalan and S. Santoso, "Wind power forecasting and error analysis using the autoregressive moving average modelling." IEEE Power & Energy Society Meeting, **(2009)**.
[16] M.S. Kandil, S. M. E. Debeiky and N. E. Hasanien, "Overview and Comparison of Long-Term Forecasting Techniques for a Fast Developing Utility: Part I", Electric Power Systems Research, vol. 58 **(2001)**, pp. 11-17.

Copyright ⓒ 2016 SERSC

Author

Harish K, Received B.E in Electrical & Electronics Engineering from RV College of Engineering, Bangalore in 2014. Currently is working as an Intern at State Load Dispatch Center, Karnataka. His area of interest include Power system operation and control, Fuzzy logic and control, Power system protection, Embedded systems, Reactive power management, Power electronics, Integration of alternative energy resources and data analytics.

 Copyright ⓒ 2016 SERSC