



# Medium-Term Minute Wise Wind Power Forecasting using Time Series Analysis

Dhanush M

PG Student, Department of Electronics & Instrumentation Engineering, Dayananda Sagar College of Engineering,  
Bangalore, India

**Abstract:** Power system operators have to predict changes in wind power production in order to schedule the spinning reserve capacity and to manage the grid operations. Wind power forecasting plays an important role in the allocation of balance power. Although the prediction accuracy of the 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 the electricity supply. This paper deals with medium term minute wise forecast of wind energy for the state grid of Karnataka by employing a simple time series analysis. . Data collected from August 8<sup>th</sup>, 9<sup>th</sup> is used to predict for the august 10<sup>th</sup> and a template is designed so that by giving any 2 days data 3<sup>rd</sup> day data can be forecasted automatically.

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

## I. INTRODUCTION

Forecasting deals with making an assessment of the future, with 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 the historical data series is simply captured and extrapolated into the future. Due to the random behaviour of the wind power productions, the output predictions of the productions are really helpful to increase the efficiency of the 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 compensation. 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 productions, which are delivered to the power system operators to suggest the electricity systems adjustment for the reserves, can reduce the cost of the short-term capacity reservations and therefore, 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].

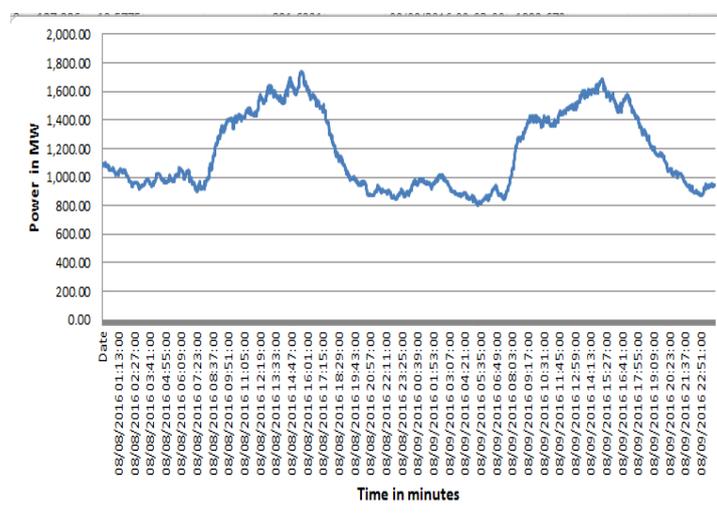


Figure 1 Minute-wise wind power data of 8<sup>th</sup> and 9<sup>th</sup> august.



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 forecasting, which is from 1 week to 1 year or more ahead are available for wind power forecasting. Minute wise wind power data collected of the state pool for the august 8<sup>th</sup> and 9<sup>th</sup> is as shown in the figure 1. This paper deals with Medium-term forecasting which plays an important role in maintenance planning and operational management.

## II. UNDERSTANDING TIME SERIES DATA

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

### Trend Pattern (T<sub>t</sub>)

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. A trend pattern is shown in the figure 2.

### Seasonal Pattern (S<sub>t</sub>)

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 fixed and known period. Seasonal pattered variation is as shown in the figure 3.

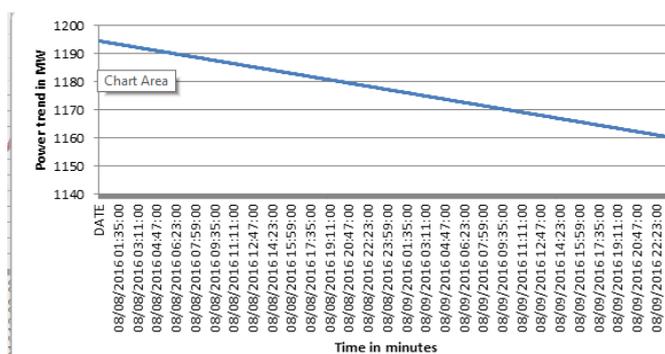


Figure 2 Trend pattern graph

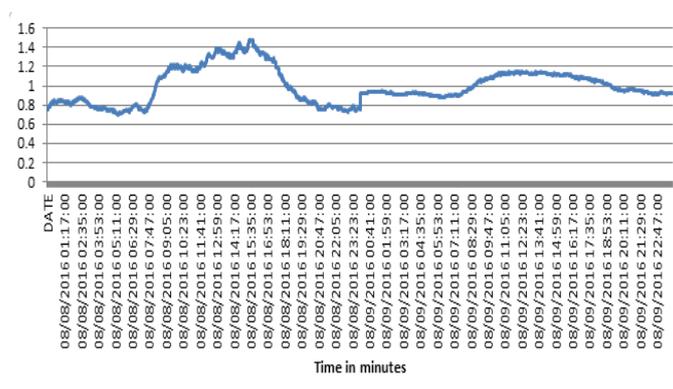


Figure 3 Seasonal variation of wind power

### Cyclic Pattern

A cyclic pattern exists when data exhibits rise and falls that are not of fixed period.

Wind power typically contains both a seasonal and trend component, if S<sub>t</sub> is the seasonal component in the data and Y<sub>t</sub> is the actual data at time t, then a multiplicative decomposition is given by equation (1).

$$Y_t = S_t \times T_t \dots\dots (1)$$



III. FORECASTING MINUTE WISE DATA

The first 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 influenced in the mean, which depicts an idea that future values will be affected only by the recent past.

$$F_{t+1} = \left(\frac{1}{k}\right) \times \sum_{i=t-k+1}^t Y_i \dots\dots (2)$$

It is called moving average of order k, MA (k). Since, the paper deals with forecasting for each day separately, k is the period of that respective day. It can be employed of the month wise also. Moving average eliminates some of the randomness in the data, leaving a smooth trend-cycle component. Period (k) is calculated with respect to minutes in a day as it is a minute wise forecast. For example one day has 24 hours, 1 hour has 60 minutes so we can say in one day (minutes\*hours) i.e. 60\*24=1440 data in a day.If month wise forecast then (minutes\*hours\*days) 60\*24\*31=44640 for January.

The next step is making the results symmetric by making use of “centred moving average (CMA)” of order 1440, which takes the average of two consecutive MA. CMA is given in the equation (3).

$$CMA_t = \left(\frac{1}{2}\right) \times (MA_t + MA_{t+1}) \dots\dots (3)$$

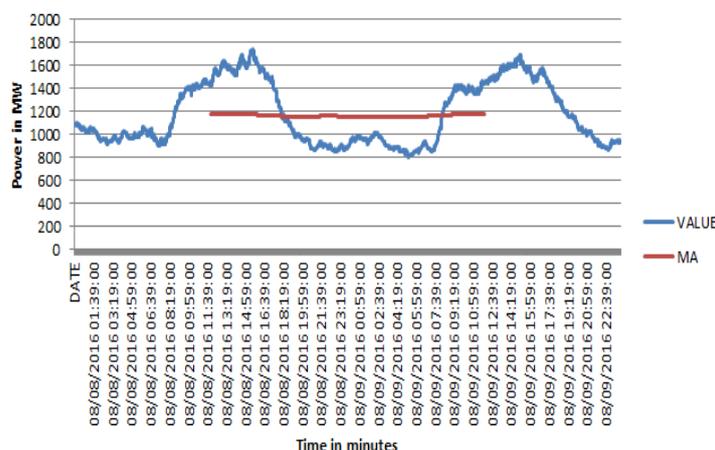


Figure 4 January forecast showing actual wind data and Moving average.

After finding the CMA or baseline for the data, we can find the seasonal and random component (S<sub>t</sub>, E<sub>t</sub>), which is given in the equation (4).

$$S_t E_t = Y_t \div CMA_t \dots\dots (4)$$

After extracting the seasonal and random component of the data, only seasonal component is extracted from it as shown in Figure 3.

Next step is to de-seasonalize the data in order to further smoothen the data for forecasting as shown in the figure 5. Using de-seasonalized components as y variable in simple linear regression, we find the trend component. Simple linear 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 ANALYSS add- in to get the output in a single step. The output obtained for the august 10<sup>th</sup> is as shown in Figure 6.





For example for the given two days, Intercept and slope are 1194.569 and -0.012 respectively as shown in Figure 7 and for the first value considered time code is 1, for 525<sup>th</sup> value time code is 525 and so on. Trend line is shown in Figure 2. Finally, the forecasted value is given by,

$$Forecast = S_t \times T_t \dots\dots (6)$$

The obtained forecast value is plotted against the actual value as shown in the figure 8. These values can be extended to the future by simple drag in excel worksheet to obtain the future forecast as shown in the figure 9.

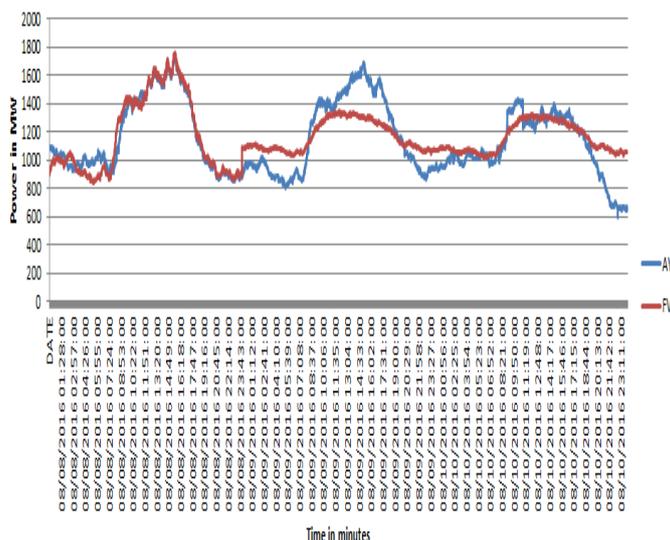


Figure8 Actual value vs forecasted value of august 8<sup>th</sup>, 9<sup>th</sup> and 10<sup>th</sup>.

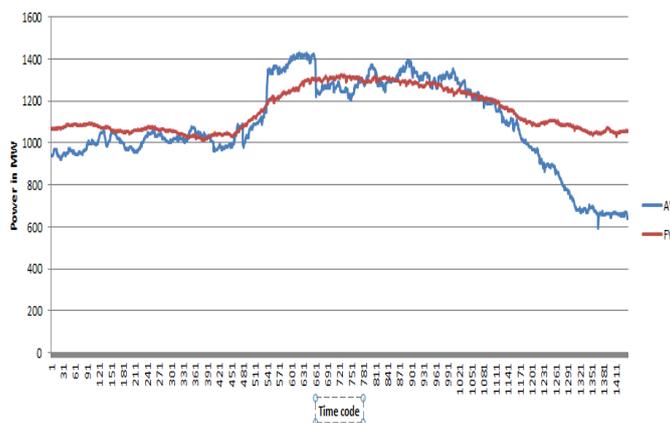


Figure9 Minute-wise Forecast Vs Actual data for 10<sup>th</sup> august

#### IV. 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 the period  $t$ , the error is given by the equation (7).

$$e_t = Y_t - F_t \dots\dots (7)$$

Mean error (ME) is an informal term that usually refers to the average of all the errors in a set and it is given by,

$$ME = (e_1 + e_2 + \dots\dots\dots + e_n) \div n \dots\dots (7)$$

Mean absolute error (MAE) is a quantity used to measure how close forecasts or predictions are to the eventual outcomes and is given by,

$$MAE = (|e_1| + |e_2| + \dots\dots\dots + |e_n|) \div n \dots\dots (8)$$



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Mean squared error (MSE) measures the average of the squares of the error and it is given by,

$$MSE = ((e_1)^2 + (e_2)^2 + \dots + (e_n)^2) \div n \dots (9)$$

Percentage error (PE) is the measure of how inaccurate a measurement is and is given by,

$$PE = \left(\frac{e_t}{Y_t}\right) \times 100\% \dots (10)$$

Mean absolute percentage error (MAPE) is given by,

$$MAPE = (|PE_1| + |PE_2| + \dots + |PE_n|) \div n \dots (11)$$

These errors quantify the accuracy of the forecast model. The mean error does not 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 [10-13].

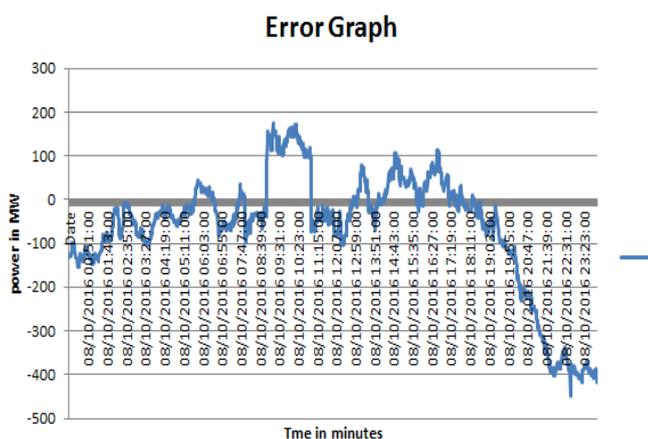


Figure 10 Error graph

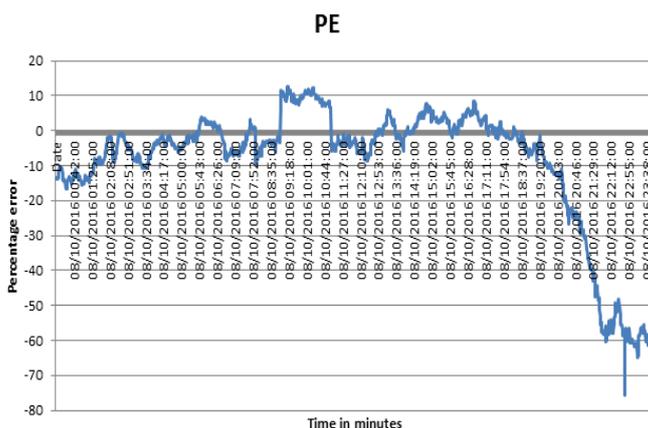


Figure 11 Percentage error graph

Table 1 Error Tabulation

DAY	ME	MPE	MAPE	MAE	MSE
August 10 <sup>th</sup>	-64.39	-8.98	11.79	102.48	22591.9

Minute wise forecasting has its own disadvantages when compared to hourly or daily forecasts, accuracy of the forecast is highly questionable sometimes [14]. Classical multiplicative model is used for forecasting in the paper. Forecasts show what is likely to happen “on average”, it is rarely perfect. So it is good to practice to complement forecasts with



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measures of the forecast uncertainty [15-16]. Errors have been tabulated as shown in Table 1 and error graph is shown in the figure 10. Percentage error graph is shown in the figure 11. The model was tested in real time at the SCADA centre from 8<sup>th</sup> to 10<sup>th</sup> august 2016 and the plot of actual data Vs Forecast data is as shown in figure 12

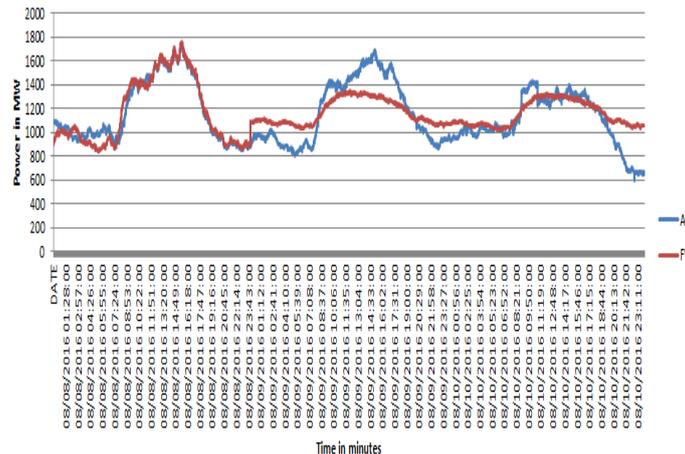


Figure 12 Minute-wise Forecast model tested with real time data from 8<sup>th</sup> to 10<sup>th</sup> august 2016.

## V. CONCLUSION

Mint wise forecast was performed using the classical multiplicative model considering each day separately. Considering the data collected from 8<sup>th</sup> to 9<sup>th</sup> august 2016, the forecast was performed for 10<sup>th</sup> august 2016. This paper clearly explains the steps involved in minute-wise forecasting. Platforms like MATLAB, Tableau and Excel were used to analyse 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 centre and the forecast value had the same trend has the actual value. 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. Hence, the classical multiplicative forecast model is tested successfully for minute-wise data.

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**BIOGRAPHY**

**Dhanush M** M.Tech in Microelectronics and Control System Engineering from Dayananda Sagar college of Engineering Bangalore. Worked as an Intern at State Load Dispatch Center (SCADA), Karnataka Power Transmission Limited (KPTCL), Karnataka