Data Analysis and Physical Modeling for Short Term Wind Speed Forecasting at Four Locations in Ireland

Prof. Parikshit G. Jamdade
Department of Electrical Engineering, PVG’s College of Engineering & Technology, Pune
Shri. Anurag V Chavan
UG Student, Department of Electrical Engineering, PVG’s College of Engineering & Technology, Pune
Shri. Jagruti J Sonawane
UG Student, Department of Electrical Engineering, PVG’s College of Engineering & Technology, Pune
Shri. Komal A Padalkar
UG Student, Department of Electrical Engineering, PVG’s College of Engineering & Technology, Pune
Shri. Rahul Shivsharan
UG Student, Department of Electrical Engineering, PVG’s College of Engineering & Technology, Pune
Prof. Shrinivas G. Jamdade
Department of Physics, Nowrosjee Wadia College, Pune

Problem statement

Wind energy has the lower cost of electricity production and it is available in ample amount. Therefore, larger numbers of countries are taking steps forward for wind power production as source for future power generation. Power demand is having varying nature because of various uncertainties, including population growth, changing technology, economic conditions, weather conditions, and general randomness in individual usage etc. It is also affected by known calendar effects due to the time of day, day of week, time of year, local event, festivals and public holidays. To satisfy the power demand we have to do resource forecasting. Wind power forecasting is one of the parts of the resource forecasting.

As wind is random in nature wind speed forecasting became main consideration. Accurate forecasting is a necessary for manager to plan effectively. Inaccurate forecasting may lead to inaccurate decisions that may lead to ineffective management in overall operations.

Wind power prediction is also a need process for

- Wind farms unit's maintenance
- Optimal power flow between conventional units and wind farms
- Electricity marketing bidding
- Power system generators scheduling
- Energy reserves and storages planning and scheduling

Many factors affect wind power prediction, includes

- Forecasting model for wind speed
- Direction at the farm site
- Historical data
- Farm layout

Problem statement

This paper is presents the methods used for the short term load forecasting ranges up to four weeks (one month) ahead based on relating the forecasted value to their corresponding historical value in previous years within the same time period. A prediction model is developed using historical data. The developed model is then used to predict the corresponding wind speed and then results are checked with the actual values.

The proposed models are characterized by

- Very simple
- Effective for few hours ahead and day a head prediction
- Independent on collected data from other sites

Approach used to solve the problem

For short term wind speed forecasting five methods are used and they are

- Moving average method (MAM)
- Linear regression method (LRM)
- Polynomial regression method (PRM)
- Transcendental regression method (TRM)
- Auto-regressive integrated moving average (ARIMA) Method

In experimentation, forecasted values are obtained for year 2014 from data's of years 1995 - 2013 and they are compared with the actual wind speed values of 2014 for checking the accuracy of the results.

Tools used

MATLAB Software for Code Building and Graph Analysis

Results achieved

Results obtained are highly accurate. From the analysis of these results we found that ARIMA is the most suitable method for short term wind speed forecasting. These results are used for further study to have accurate designs of wind power installations and to develop wind power plant.

Abstract

In a long-term planning, power system planners are using probabilistic method to access wind power generation while short term wind speed forecasting plays an important role in load management. For short term wind speed forecasting synthesis methods are used. In this paper for modeling and data analysis, synthesis methods used are moving average method (MAM), linear regression method (LRM), polynomial regression method (PRM), transcendental regression method (TRM), auto-regressive integrated moving average (ARIMA) Method. In experimentation, forecasted values are obtained for year 2014 from data's of years 1995 - 2013 and they are compared with the actual wind speed values of 2014 for checking the accuracy of results. From analysis of these results we found that ARIMA is the most suitable method for short term wind speed forecasting.

Keywords

Moving Average Method (MAM); Linear Regression Method (LRM); Polynomial Regression Method (PRM); Transcendental Regression Method (TRM); Auto Regressive Integrated Moving Average (ARIMA) Method.

In this study, data set of years 1995 to 2014 are obtained containing mean wind speed of each month in a year with observation height of 50 m above ground level.

The chosen stations from Ireland are

Location	Latitude N°	Longitude W°
Malin Head Co. Donegal	55°23'N	07°23'W
Dublin Airport Co. Dublin	53°21'N	06°15'W
Belmullet Co. Mayo	54°14'N	09°58'W
Mullingar Co. Westmeath	53°31'N	07°21'W

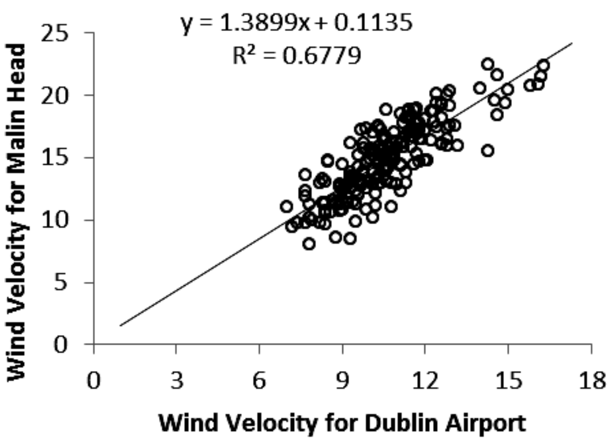
Table 1

Location	Mean Wind Speed
Malin Head Co. Donegal	15.02
Dublin Airport Co. Dublin	10.6
Belmullet Co. Mayo	12.34
Mullingar Co. Westmeath	6.699

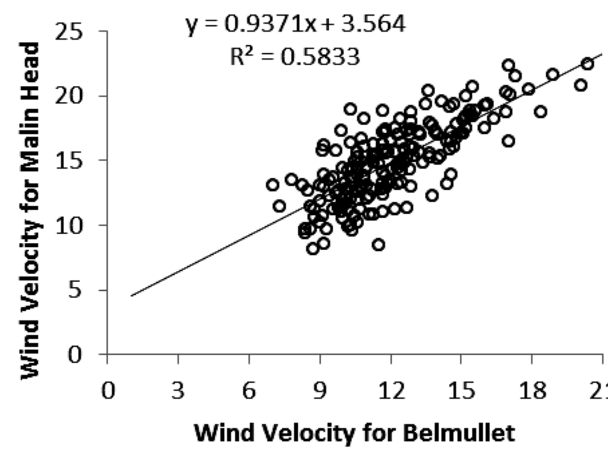
Table 2

For analysis, forecasted values are obtained from the data spanning from years 1995 to 2013 which is easily available on Irish meteorological website and they are compared with the actual wind speed values of 2014 for scrutinizing the accuracy of results.

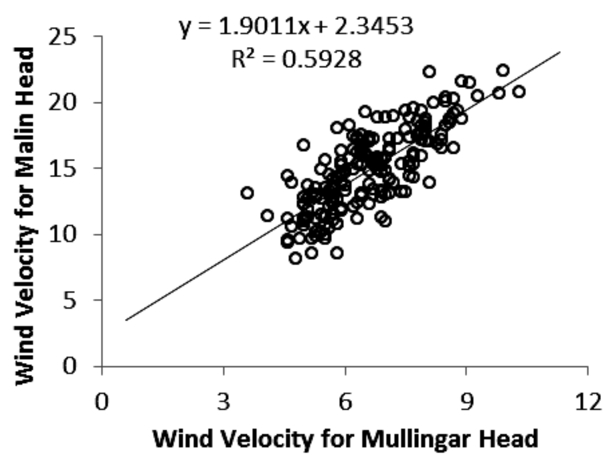
Figures are showing the relative variation in wind speed of Dublin Airport, Belmullet and Mullingar sites with respect to wind speed for locations Malin Head, respectively for 20 years.



Relative Variation in Wind Speed of Dublin Airport with the Wind Speed of Malin Head



Relative Variation in Wind Speed of Belmullet with the Wind Speed of Malin Head



Relative Variation in Wind Speed of Mullingar with the Wind Speed of Malin Head

Moving Average Method (MAM)

Sometimes, use of old data might no longer be relevant so we are using this method. This method uses the average of the data to predict next value called as forecasted value, i.e. we calculate the mean using only k latest observations as

$$F_{t+1} = \frac{1}{k} \sum_{i=t-k+1}^{t} Y_i$$

As the new data becomes available, the oldest observation is dropped and the latest included. Here forecast is easily updated from period to period. A disadvantage of this method is that it places as much weight on $X_{t(n-1)}$ as on X_t.

Linear Regression Method (LRM)

Here we assume a linear relationship exist between Y and X. so that

$$Y = a + bX + e_i$$

Where a is intercept, b is the slope of the line and e is error due to deviation of the observation from the linear relationship. This is the ordinary least-squares estimation.

Where

$$b = \frac{\sum_{i=1}^{n}(X_i - X)\ (Y_i - Y)}{\sum_{i=1}^{n}(X_i - X)^2}$$

$$a = Y - bX$$

Let the vertical deviation (errors) be denoted by

$$e_i = Y_i - Y$$

Polynomial Regression Method (PRM)

PRM is most suitable for non-linear data values. The least squares technique can be readily used to fit the data to a polynomial.

Consider a polynomial of degree m-1

$$Y = a_1 + a_2 X + a_3 X^2 + \ldots\ldots\ldots + a_n X^{m-1}$$

$$Y = f(X)$$

If the data is having m sets of X and Y values, then the sum of squares of the errors is given by

$$Q = \sum_{i=0}^{n} [Y_i - f(X_i)]^2$$

Where f(X) is a polynomial containing coefficients a_1, a_2, a_3, etc…, we have to calculate all the n coefficients.

So we have to solve n equations to get these coefficients

$$\frac{\partial Q}{\partial a_1} = 0 \quad \frac{\partial Q}{\partial a_2} = 0 \ldots\ldots\ldots \quad \frac{\partial Q}{\partial a_m} = 0$$

Consider a general term,

$$\frac{\partial Q}{\partial a_j} = \sum_{k=0}^{n} [Y_i - f(X_i)] \times \frac{\partial f(X_i)}{\partial a_j} = 0$$

$$\frac{\partial f(X_i)}{\partial a_j} = X_i^{\,j-1}$$

Thus, we have

$$\sum_{i=1}^{n} [Y_i - f(X_i)] X_i^{\,j-1} = 0$$

Polynomial Regression Method (PRM)

$$\sum\left[Y_i X_i^{\,j-1} - X_i^{\,j-1} f(X_i)\right] = 0$$

Substituting for f (X_i)

$$\sum_{i=0}^{n} X_i^{\,j-1}\left(a_1 + a_2 X_i + \ldots . + a_m X_{i\,m-1}\right)$$

$$= \sum_{i=0}^{n} Y_i X_i^{\,j-1}$$

These are n equations (j = 1, 2….m) and each summation is for i = 1 to n

$$a_1 n + a_2 \sum X_i + a_3 \sum X_i^{2} + \ldots . . + a_m \sum X_i^{\,n-1} = \sum Y_i$$

$$a_1 \sum X_i + a_2 \sum X_i^{2} + a_3 \sum X_i^{3} + \ldots \ldots + a_m \sum X_i^{m} =$$
$$\sum Y_i X_i$$

$$a_1 \sum X_i^{\,m-1} + a_2 \sum X_i^{m} + a_3 \sum X_i^{\,m+1} + \ldots \ldots$$
$$\ldots + a_m \sum X_i^{\,2m-2} = \sum Y_i X_i^{\,m-1}$$

The set of m equations can be represented in matrix notation as follows

$$CA = B$$

Where, The element of matrix C is

$$C(j,k) = \sum_{i=0}^{n} X_i^{\,j+k-2}$$

Similarly,

$$B(j) = \sum_{i}^{n} Yi\, X_i^{\,j-1}$$

Transcendental Regression Method (TRM)

The relationship between the dependent and independent variables is not always linear. The nonlinear relationship between data points can be represented in the form of transcendental equations (or higher order polynomials). Here nonlinear model is used for wind speed forecasting which is given as

$$p = a\,X^{b}$$

Where p are the wind speed values for corresponding variable wind speed values (v), we can then calculate the parameters a and b.

Using least square method, the sum of the squares of all errors can be written as

$$Q = \sum_{i=0}^{n}\left[p_i - a\,X_i^{\,b}\right]^2$$

To minimize Q, we have

$$\frac{\partial Q}{\partial a} = 0 \quad \frac{\partial Q}{\partial b} = 0$$

We can prove that

$$\sum p_i X_i^{\,b} = a \sum \left(Y_i^{\,b}\right)^2$$

$$\sum p_i X_i^{\,b} \ln X_i = a \sum \left(Y_i^{\,b}\right)^2 \ln X_i$$

This equations can be solved for a and b. But since b appears under the summation sign, an iterative procedure is used for obtaining a and b.

The equation using the conventional variables X and Y as

$$Y = a\,X^{b}$$

Transcendental Regression Method (TRM)

Taking logarithm on both the sides, we get

$$\ln Y = \ln a + b \ln X$$

This equation is similar in form to the linear equation and, therefore, using the same procedure we can calculate the parameters a and b

$$b = \frac{n \sum \ln X_i \ln Y_i - \sum \ln X_i \sum \ln Y_i}{n \sum (\ln X_i)^2 - (\ln \sum X_i)^2}$$

$$\ln a = R = \frac{1}{n}\left(\sum \ln Y_i - b \sum \ln X_i\right)$$

$$a = e^R$$

Similarly, we can linearize the exponential model by taking logarithm on both the sides. This would yield $\ln p = \ln p_0 + kt \ln e$

Since,

$$\ln e = 1$$

We have $\ln p = \ln p_0 + kt$

This is similar to the linear equation

$$Y = a + bX$$

Where

$$Y = \ln p \qquad a = \ln p_0$$

b = k, X = t

We can easily calculate a and b and then p_0 and k

Auto Regressive Integrated Moving Average (ARIMA) Method

The forecasted variables are depends on the past observations then we can write the relationship as

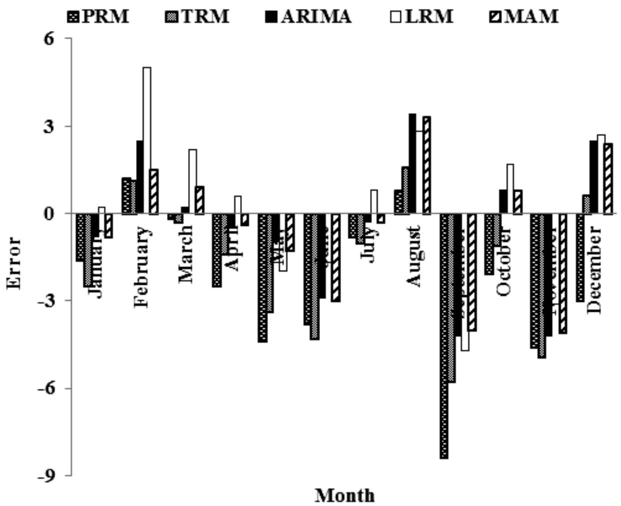
$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-2} + \ldots + b_n Y_{t-p} + e_t$$

The RHS of eqn. contains time-lagged values of the forecasted variable.
Differencing can remove non-stationary in a series of forecasted values. The first order difference is given by

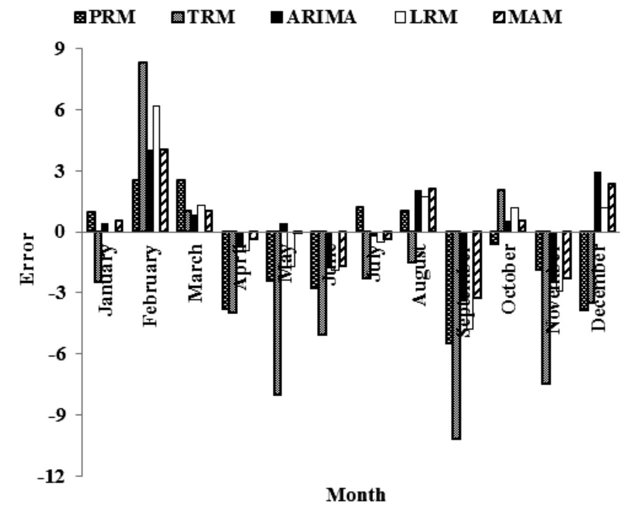
$$Y_t^1 = Y_t - Y_{t-1}$$

Results

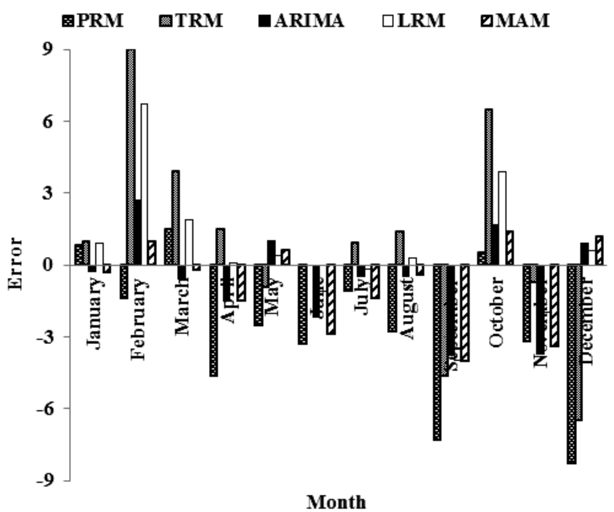
The results presented in table 3, table 4, table 5 and table 6 shows the actual value (AV) and forecasted value of wind speed for different methods for locations Malin Head, Dublin Airport, Belmullet and Mullingar sites respectively. From these tables error in wind speed for each month was calculated which shows that the error difference is lesser in the values given by ARIMA method as compared to the others. This indicates that, due to the presence of mathematical iterations in calculating forecasted values, the accuracy of ARIMA method is better as compared to other methods. Figures are showing the error in wind speed for each month using different methods for locations Malin Head, Dublin Airport, Belmullet and Mullingar sites respectively. These figures are showing additive trend with seasonal effect. Time series models are fairly accurate for wind speed forecasting applications. These are used for long term forecasts as well as for very short term forecasts. One of the disadvantage of these methods for short term forecast is that they are unable to predict accurately the nonlinear characteristics between wind speed and time duration.
This paper suggests that ARIMA method is most suitable for short term wind speed forecasting as it gives error values, while moving average method (MAM) is the second best method.



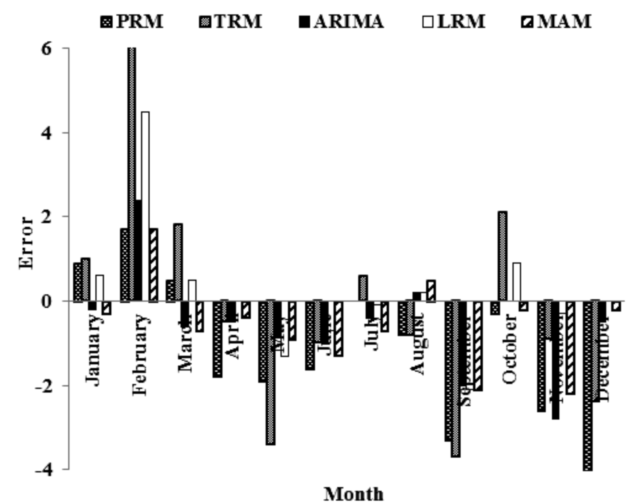
Error in Wind Speed for Location Malin Head with Months



Error in Forecasted Wind Speed for Location Dublin Airport with Months



Error in Wind Speed for Location Belmullet with Months



Error in Wind Speed for Location Mullingar with Months

Month	AV	MAM	SRM	PRM	TRM	ARIMA
Jan	16.9	17.7	16.7	18.5	19.4	17.7
Feb	19.3	17.8	14.3	18.1	18.2	16.8
Mar	16.9	16	14.7	17.1	17.2	16.7
Apr	13.9	14.3	13.3	16.4	15.3	14.36
May	12	13.3	14	16.4	15.4	12.96
Jun	9.3	12.3	11	13.1	13.6	12.2
Jul	11.3	11.6	10.5	12.1	12.35	11.6
Aug	15.3	12	12.5	14.5	13.7	11.9
Sep	10.2	14.2	14.9	18.6	16	14.43
Oct	16.7	15.9	15	18.8	17.8	15.9
Nov	13.2	17.3	16.3	17.8	18.15	17.4
Dec	19.6	17.2	16.9	22.6	19	17.1

Table 3

Month	AV	MAM	SRM	PRM	TRM	ARIMA
Jan	12.7	12.2	12.7	11.76	15.21	12.3
Feb	15.9	11.9	9.7	13.4	7.6	11.9
Mar	12.1	11.1	10.8	9.6	11.1	11.3
Apr	9.8	10.2	10.7	13.6	13.8	10.4
May	9.9	10	11.6	12.3	17.9	9.51
Jun	7.6	9.3	9.5	10.4	12.7	9.3
Jul	8.7	9.1	9.2	7.5	11	8.9
Aug	11.4	9.3	9.7	10.4	12.9	9.4
Sep	6.5	9.8	11.3	12	16.7	9.9
Oct	11.5	11	10.3	12.1	9.5	11
Nov	9.1	11.4	12	11	16.6	11.5
Dec	13.9	11.6	12.7	17.8	17.4	11

Table 4

Month	AV	MAM	SRM	PRM	TRM	ARIMA
Jan	13.9	14.2	13	13.1	12.9	14.2
Feb	15.3	14.3	8.6	16.7	6.3	12.6
Mar	12.5	12.7	10.6	11	8.6	13.1
Apr	10.3	11.8	10.2	14.9	8.8	11.8
May	12	11.4	11.6	14.5	12.9	11
Jun	8.3	11.2	9.4	11.6	8.3	10.5
Jul	9.1	10.5	9.3	10.2	8.19	9.6
Aug	10.2	10.6	9.9	13	8.8	10.7
Sep	7.6	11.6	11.6	14.9	12.2	11.4
Oct	14.1	12.7	10.2	13.6	7.6	12.4
Nov	9.6	13	11.6	12.8	10.3	13.3
Dec	14.6	13.4	14	22.9	21.1	13.7

Table 5

Month	AV	MAM	SRM	PRM	TRM	ARIMA
Jan	7.3	7.6	6.7	6.4	6.3	7.5
Feb	9.3	7.6	4.8	7.6	3.2	6.9
Mar	6.6	7.3	6.1	6.1	4.8	7.2
Apr	6.3	6.7	6.3	8.1	6.8	6.8
May	5.6	6.5	6.9	7.5	9	6.4
Jun	4.6	5.9	5.3	6.2	5.6	5.6
Jul	4.9	5.6	5	4.9	4.3	5.3
Aug	5.7	5.2	5.5	6.5	6.5	5.5
Sep	3.9	6	6	7.2	7.6	5.9
Oct	6.5	6.7	5.6	6.8	4.4	6.5
Nov	5.2	7.4	5.5	7.8	6.1	8
Dec	6.8	7	6.8	11	9.2	7.3

Table 6

References

- M. A. Matos and R. J. Bessa, Setting the operating reserve using probabilistic wind power forecasts, IEEE Trans. Power Syst., 26 (2),pp. 594 -603, 2011.
- E. Erdem and J. Shi, “ARMA based approaches for forecasting the tuple of wind speed and direction,” Appl. Energy, vol. 88, no. 4, pp. 1405–1414, Apr. 2011.
- Corberan-Vallet, A., Bermudez, J. D., and Vercher, E., “Forecasting correlated time series with exponential smoothing Models”. International Journal of Forecasting, Vol. 27, pp 252-265, 2011.
- R. J. Bessa , V. Miranda , A. Botterud , Z. Zhou and J. Wang, Time-adaptive quantile copula for wind power probabilistic forecasting, Renew. Energy, 40 (1), pp. 29-39, 2012.
- S. G. Jamdade and P. G. Jamdade, Extreme Value Distribution Model for Analysis of Wind Speed Data for Four Locations in Ireland, International Journal of Advanced Renewable Energy Research, 1 (5), pp. 254–259, 2012.
- A. M. Foley, P.G. Leahy, A. Marvuglia, E. J. McKeogh, Current Methods and Advances in Forecasting of Wind Power Generation, Renewable Energy, 37(1), pp. 1-8, 2012.
- A. Khosravi, S. Nahavandi and D. Creighton, Prediction intervals for short-term wind farm power generation forecasts, IEEE Trans. Sustain. Energy, 4 (3), pp. 602-610, 2013.
- S. M. Weekes and A. S. Tomlin, Low-cost wind resource assessment for small-scale turbine installations using site pre-screening and short-term wind measurements, Renewable Power Generation, IET, 8 (4), pp. 348–358, 2014.
- P. G. Jamdade and S. G. Jamdade, “Evaluation of wind energy potential for four sites in Ireland using Weibull distribution model”, J. Power Technol, 1(95), pp. 48–53, 2015.
- Balagurusamy, “Numerical Methods”, Tata McGraw Hill Publication,1999.
- P. G. Jamdade and S. G. Jamdade, “Power System Planning and Reliability”, TechMax Publication, ISBN - 978-93-5224-202-3, Jan. 2016.