ARIMA Modeling of Wind Speed for Wind Farm Reliability Analysis

Rajeevan .A.K
Division of Electrical Engineering, School of Engineering, Cochin University of Science and Technology (CUSAT), Cochin, Kerala, India

P.V.Shouri
Department of Mechanical Engineering, Model Engineering College, Cochin, Kerala, India.

Usha Nair
Division of Electrical Engineering, School of Engineering, Cochin University of Science and Technology (CUSAT), Cochin, Kerala, India

Abstract—**The output power of a wind energy conversion system (WECS) fluctuates with wind speed variations. Accurate wind speed modeling is essential to forecast wind power changes in a site. This paper is intended to develop an autoregressive integrated moving average (ARIMA) time series model for wind speed. In ARIMA time series modeling, it is possible to change a nonstationary time series to a stationary time series by taking differences. A wind speed collection of one year from a 99MW wind farm situated in Theni, Tamil Nadu, India is used in this modeling. The developed model is used to evaluate annual reliability indices like loss of load probability (LOLP), loss of load expectation (LOLE), and loss of energy expectation (LOEE) by convolving wind farm generation model with load model of the grid. Furthermore, variations of LOLE and reliability with changes in peak load are carried out. The study illustrates that system risk index LOLE improves with decrease in peak load and WECS has high reliability to meet the changes in peak load.**

Keywords—ARIMA, LOLE, reliability, wind speed, wind power.

I. INTRODUCTION

Wind power generation is one of the most accomplished technologies to enhance the production of green energy. Due to its vast environmental and social benefits along with the policies adopted by governments, wind became the most promising and encouraging alternative source. In the last few decades wind power generation shows tremendous growth and is all set to increase in future. The integration of wind energy should have concern about the reliability of grid, since bulk integration may affect the reliability indices.

The output power of a wind energy conversion system is a stochastic process. There exist a non linear relationship between wind speed and power developed. Because of this non linear characteristics the wind energy developed by a WECS, which cannot be compared with conventional systems. In power system analysis there are various reliability indices like LOLE, LOLP, LOEE and energy index of reliability (EIR) which is used to access the reliability of a system [1]. A general and better model for reliability benefit evaluation of power system containing grid integrated wind power system using time series ARMA model has been presented in [2,3]. Here evaluation has been done by considering various reliability indices such as LOLE, LOLP and LOEE.

Reference [4] presents LARIMA model for wind power generation, which can be applied in reliability evaluation of power system with wind energy. Using this model, synthetic wind power time series can be generated which are used in sequential Monte Carlo simulations to assess the adequacy of the power system generation to meet future load demand. The effect of different possible operations for a wind farm with energy storage on the reliability indices are evaluated using Roy Billinton Test System (RBTS). A Monte Carlo Simulation (MCS) method is used here to identify the chronological random nature of wind speed in the adequacy assessment of a generating system including wind power and battery storage.

An analytical method for reliability evaluation is presented in [5]. Here a CCOPT is developed for a single turbine power output, and then FCCOPT, the CCOPT for the wind farm is developed. This approach is applied to RBTS to study about the impact of wind power on generation system adequacy. The RBTS which is modified with installed capacity of 240MW and peak load of 185MW is used to study the effect of load on wind distribution in reliability evaluation.

This paper intends to develop an ARIMA based wind speed model for Theni wind farm in India. The proposed method is adequate for finding annual reliability indices such as LOLP, LOLE and LOEE, by combining wind farm COPT with load model. Apart from that the reliability of the wind farm and variations in system risk index LOLE are evaluated against changes in peak load. The result of this analysis, if used in wind power planning and scheduling helps to improve the overall reliability of wind integrated power system.

II. ARIMA WIND SPEED MODELING

The measured values of wind speed as a time series from Theni in Tamil Nadu state is utilized in this paper. The measurements time interval is ten minute with a record of one

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year (2011) [6]. The hourly values of wind speeds are calculated by averaging six consecutive ten minute values of wind data. This is depicted in Fig.1. The observed wind speed time series is nonstationary. To convert a nonstationary time series to a stationary time series we take first difference. Differencing tends to remove short and long term trends in a time series and is therefore used to achieve stationarity [7]. The time series plot of first difference wind speed pattern is shown in Fig.2. Autocorrelation plot and partial autocorrelation plot of the first differenced time series is plotted in Fig.3.

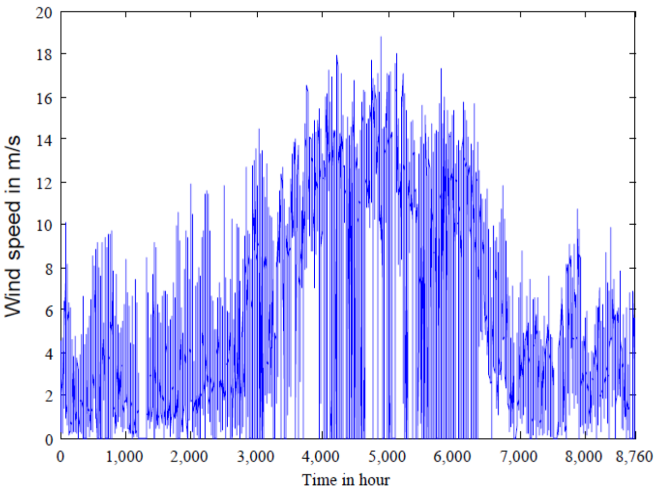

Figure1: Wind speed time series for Theni wind site in 2011.

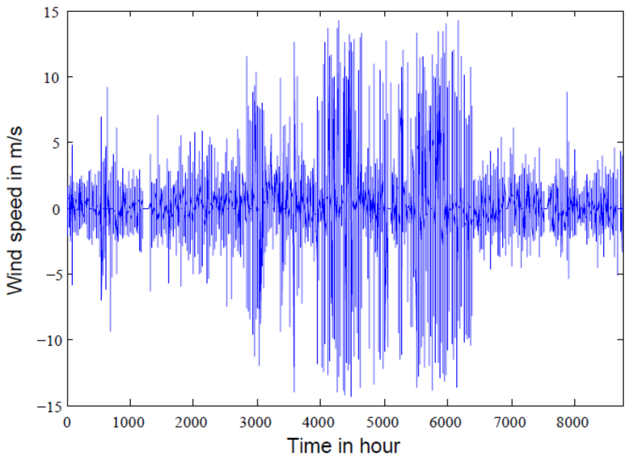

Figure 2: First difference time series of observed wind speed

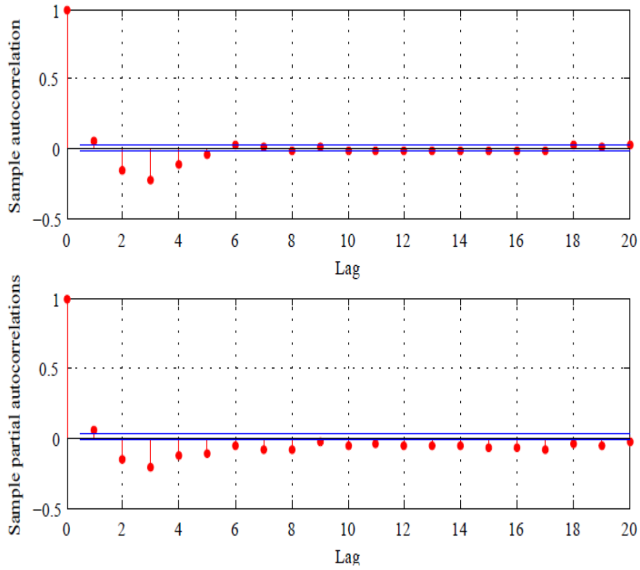

Figure 3: Autocorrelation functions of first difference series

Autocorrelation coefficients are the key statistics in time series analysis; they are used to evaluate relationship among series values. Autocorrelation at lag 1 is the correlation between the original series x_t and the same series moved forward by one period. The autocorrelation of stationary data reduce to zero comparatively quickly, while for a nonstationary time series they are significantly apart from zero for many time lags [7]. This indicates that, the first difference wind speed data attains stationarity. The average value and standard deviation of measured wind data is 5.87m/s and 4.70 respectively. The ARIMA (1, 1, 2) model is identified as the best fitted time series model for the Theni wind site. The coefficients calculated for the site are given in equation (1). Here conditional probability distribution is Gaussian.

$$y_t = -0.28002 y_{t-1} - 0.64216\, e_{t-1} - 0.35784\, e_{t-2} \quad (1)$$

Where $e_t \in N(0, 2.40097^2)$

Where e_t represent a white noise whose mean is zero and variance is 2.40097^2.

III. Wind Speed Simulation

$$\text{Let,} \quad y_t = \frac{ow_t - \mu_t}{\sigma_t} \quad (2)$$

Where

ow_t = measured wind speed,

μ_t = mean of the above wind data

σ_t = standard deviation of the measured wind data and

sw_t = simulated wind speed

$$sw_t = \mu_t + \sigma_t \times y_t \quad (3)$$

To examine the accuracy of the identified ARIMA (1,1,2) equation, many properties of the sw_t were compared with those of measured data. The observed mean wind speed is 5.87 m/s while that of simulated data is 6.3 m/s. The observed wind speed has a standard deviation of 4.7, while that of simulated wind speed is 4.9. Fig.4 explains the degree of matching of the observed and simulated wind speed probability distributions using the ARIMA (1.1.2) model and 8000 simulated hours. It is observed that the two curves are matching and the ARIMA (1, 1, 2) model is the best way of representing the observed wind pattern.

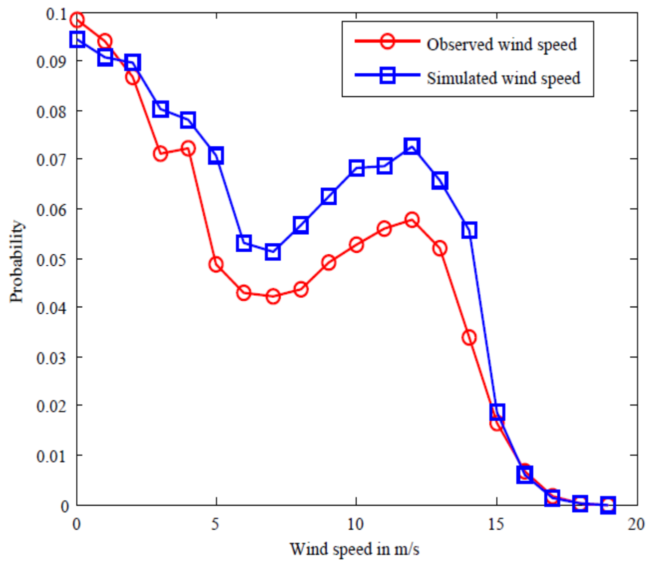

Figure.4: Probability versus wind speed.

IV. Wind Turbine Power Modeling

The wind turbine power generation primarily depends on wind pattern of the location and the characteristics of wind turbine. The operational parameters commonly used are cut- in wind speed (V_{ci}), rated wind speed (V_r) and cut- out wind speed (V_{co}). WTG rated (p_r) at 1.65 MW manufactured by Vestas (V82, 1.65MW) with cut- in, rated and cut- out wind speeds of 3.5m/s, 13m/s and 20m/s respectively are used in this analysis. The output power of a WTG on hourly basis can be calculated from the simulated hourly wind speed values with the help of following equation.

$$P(SW_t) = \left\{ \begin{array}{ll} 0 & 0 \le SW_t < V_{ci} \\ (A + B \times SW_t + C \times SW_t^{\,2}) \times P_r & V_{ci} \le SW_t < V_r \\ P_r & V_r \le SW_t < V_{co} \\ 0 & SW_t \ge V_{co} \end{array} \right\} \quad (4)$$

V. Capacity Outage Probability Table

In power system reliability assessment, conventional units are generally modeled by a two state Markov model. The output power of a WTG varies continuously from zero to the rated power, and so it requires a multistate model. A wind farm generally consists of a large number of identical WTG units and all share the same wind pattern. To develop a power output model for a wind farm, the power generation from all the WTG units is to be added up. A capacity outage probability table (COPT) represents a sequence of different capacity levels and associated probabilities [1]. It is observed that a five state COPT is enough in capacity adequacy assessment of wind integrated power system [8]. In this work, hourly power outputs were classified into 11 states and their corresponding probabilities were calculated. Table I shows that probability of having full WTG output (zero percentage capacity outage) is comparatively low for this wind pattern. The reliability indices are not much changed by the Forced Outage Rate (FOR) of WTG [9]. So it is not included in this calculation.

Table I: COPT For Wind Farm

Capacity out (MW)	Capacity in (MW)	Individual probability
0	99	0.30255
5	94	0.07679
21	78	0.05636
49	50	0.07208
69	30	0.04801
74	25	0.05130
79	20	0.04218
84	15	0.03467
89	10	0.07019
95	4	0.05226
99	0	0.19361
		1.00000

VI. Reliability Analysis

The various probabilistic concepts which are used for reliability evaluation in power system planning are loss of load probability, loss of load expectation and loss of energy expectation. Load data is essential to calculate the risk evaluation. Commonly used load models are load duration curve and daily peak load variation curve. In load duration curve approach, the individual hourly load data are used. An annual load duration curve is used in this analysis. The COPT shown in table I is combined with system load characteristics to give an expected risk of load loss.

LOLP is expressed as the probability that load is more than the available power generation. This is a probabilistic index. A loss of load occurs when load is more than available generation. LOLE is the most commonly used and accepted probabilistic method in risk analysis. LOLE can be calculated as [1].

$$LOLE = \sum_{k=1}^{N} p_k \, t_k \tag{5}$$

Where N = The number of cases for which the generation outage is more than the reserve available.

p_k = The probability of the generation outage O_k

t_k = The period of lost load in generation outage O_k

LOEE parameter is used to access the generation system reliability. LOEE is given as [1].

$$LOEE = \sum_{k=1}^{N} E_k \, p_k \tag{6}$$

Where E_k = Energy curtailed by the capacity outage O_k

The total energy demand is calculated by computing the area under the load duration curve.

The installed capacity of the wind farm under consideration is 99MW. The hourly average power generation of the wind farm in year 2011 is 22MW. This quantity is too low in comparison with installed wind farm capacity, because of the uncertainty in wind speed and the wind turbines availability etc. For risk analysis, knowledge of load duration curve is essential. Since wind farm provides power to the utility grid, it is better to apply the analysis to the load duration curve for the utility grid. Load pattern is a crucial factor in the risk analysis of generation system containing wind farm. To separate the contribution of wind farm from other sources, the load duration curve is scale down in such a manner that the maximum demand of the grid is equal to hourly average power generation of the wind farm. Here the hourly average power generation is 22MW which is taken as the peak load.

VII. Results and Discussion

Fig. (5) demonstrates system load pattern . The study period in this case is assumed to be one year and therefore 100 percentage on x- axis in Fig.(5) corresponds to 8760 hours. The annual reliability indices are obtained by comparing the peak load demand 22MW with corresponding annual load duration curve and the values are shown in table II. Risk analysis is carried out for different peak load values and is given in table III. Fig.(6) demonstrates the variations in risk with system peak load and is found that risk index increase with increase in peak load.

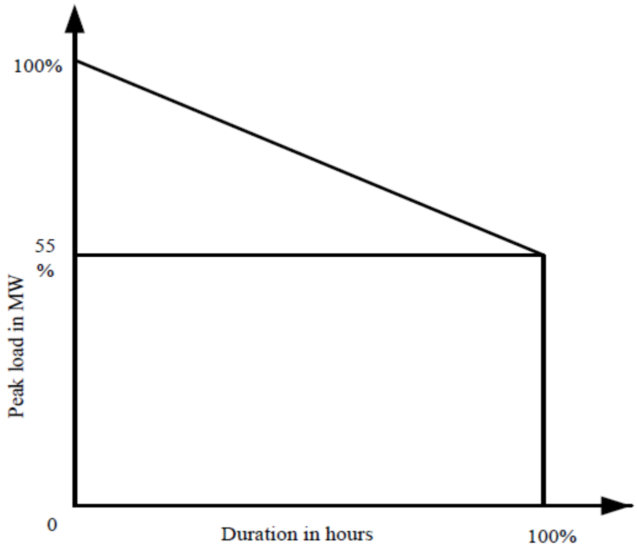

Figure.5: System load duration curve

TABLE II: ANNUAL RELIABILITY INDICES

LOLP	LOLE in hours/year	LOEE in MWh
0.3491	2178.3220	457.2130

The percentage reliability can be calculated as

$$Reliability\ in\ percentage = \frac{Number\ of\ hours - LOLE}{Number\ of\ hours} \times 100$$

Annual reliability corresponding to different peak load values is calculated and is given in table III. Fig.7 depicts the changes in reliability with changes in peak load. It is found from Fig.7 that reliability improves with decrease in system peak demand.

TABLE III: LOLE AND RELIABILITY VARIATIONS WITH RESPECT TO CHANGES IN PEAK LOAD

Peak load in MW	LOLE in hours/year	Reliability in percentage
22	2178.3220	75.13
20	2092.2720	76.12
18	2044.8360	76.66
16	1930.4000	77.96
14	1812.3520	79.31

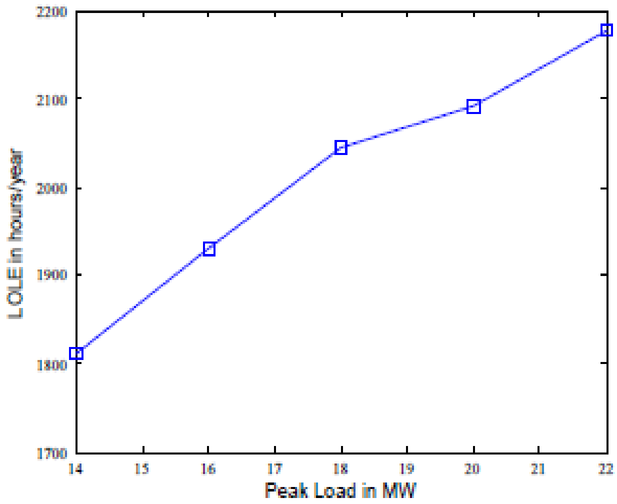

Figure.6: LOLE versus system peak load

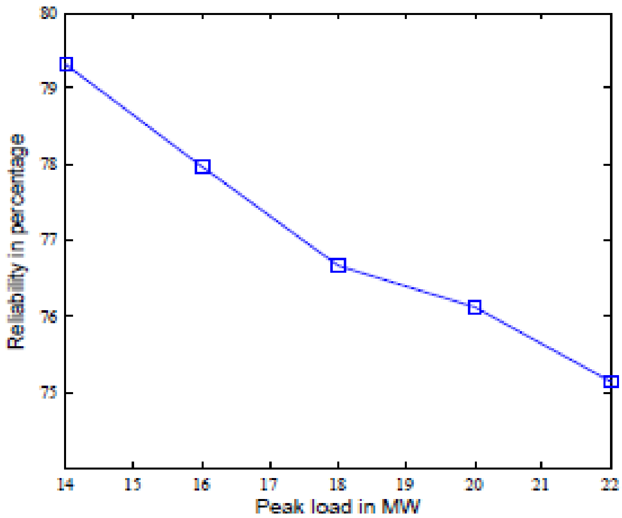

Figure.7: Reliability versus system peak load

VIII. CONCLUSION

An ARIMA based wind speed model using data from Theni wind farm in India is presented. ARIMA wind speed model provides better accuracy compared to ARMA modeling. The annual reliability indices LOLP, LOLE and LOEE are calculated by convolving wind farm generation model with load model. Variations in system risk index with changes in peak load are evaluated and it is found that risk index improves with decrease in peak load. Reliability analysis revealed that for 50 percentage change in peak load, the change in reliability is only 8.5 percentages. So it is concluded that the WECS has high reliability to meet the changes in peak load. The result of the analysis if used in wind power planning and scheduling helps to increase the overall reliability of wind integrated generating system.

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