J. Wind Eng. Ind. Aerodyn. 145 (2015) 229–236

Contents lists available at ScienceDirect

Journal of Wind Engineering and Industrial Aerodynamics

journal homepage: www.elsevier.com/locate/jweia

Wind speed prediction for wind farm applications by Extreme Value Theory and Copulas

Guglielmo D'Amico [a], Filippo Petroni [b,*], Flavio Prattico [c]

[a] Dipartimento di Farmacia, Università 'G. D'Annunzio' di Chieti-Pescara, 66013 Chieti, Italy
[b] Dipartimento di Scienze Economiche ed Aziendali, Università degli studi di Cagliari, 09123 Cagliari, Italy
[c] Dipartimento di Ingegneria Industriale e dell'Informazione e di Economia, Università degli studi dell'Aquila, 67100 L'Aquila, Italy

ARTICLE INFO

Article history:
Received 12 May 2014
Received in revised form
15 June 2015
Accepted 28 June 2015
Available online 24 July 2015

Keywords:
Wind speed
Weibull distribution
Generalized Pareto distribution
Compound Poisson process

ABSTRACT

In this paper we use risk management techniques to evaluate the effects of some risk factors that affect the energy production of a wind farm. We focus our attention on three major risks: wind speed variability, wind turbine failures and correlations between produced energy.

As a first contribution, we show that the Weibull distribution, commonly used to fit recorded wind speed data, underestimates rare events. Therefore, in order to achieve a better estimation of the tail of the wind speed distribution, we advance a Generalized Pareto distribution. We considered one aspect of the wind turbines reliability by modeling their failure events as a compound Poisson process. Finally, the use of Copula enables us to consider the correlation between wind turbines that compose the wind farm. Once this procedure is set up, we show a sensitivity analysis and we also compare the results from the proposed procedure with a simplistic energy prediction using the Weibull distribution.

1. Introduction

Wind power now accounts for a high proportion of generation capacity in many regions. For example, wind accounted for 17% of Germany's 167.8 GW of installed generation capacity in 2011 (Hau and Von Renouard, 2013). As wind power's share of electricity generation has increased, so have the financial consequences of risks associated with its inherently high variability. Wind speed variability has many financial consequences. Low wind speeds reduce generation and revenues for wind power generators and may adversely affect the ability to meet debt payments creating credit risks for investors. Conversely, excessively high wind speeds may temporarily halt generation or delay wind farm construction. When wind has priority access to the grid, thermal power plants have to balance generation regardless of whether wind is above or below forecasted levels. Wind speed variability may also compound price risk for other market players through its influence on wholesale electricity market clearing prices in competitive day-ahead and intraday markets. The uncertainty in wind power production needs to be hedged through risk management techniques.

In this work we will focus our attention on the sources of risk which are present in a wind farm, namely wind speed variability, wind turbine failures and correlation between produced energy.

Despite the Weibull distribution (WD) is often used by practitioners and researchers alike (see Weisser, 2003; Akdağ and Dinler, 2009; Chang, 2011) it does not fit well the right tail of the wind speed distribution underestimating strong wind probabilities. The WD models accurately the body of the wind speed distribution, but the same statement cannot be made for the tail of the distribution. By applying Extreme Value Theory we will show that it is possible to better estimate the number of strong wind events if a Generalized Pareto distribution (GPD) is used to fit the right tail of the wind speed distribution. A similar approach was already used in the field of wind speed modeling (see Morgan et al., 2011; Holmes and Moriarty, 1999; Van de Vyver and Delcloo, 2011; Zachary et al., 1998). Here we are interested in highlighting the importance of Extreme Value Theory as a mean for controlling the risk arising from the variability of wind speed when applied to a real case of energy production.

Another source of risk is the failure of the wind turbine and the necessary time to repair it. We model the failure events by means of a compound Poisson process. The compound Poisson model is widely adopted by insurance modelers for measuring aggregate risks (see e.g. Tse, 2009) and we will show that it can be used also in the management of a wind farm to consider periods of non-production of energy due to failure of the wind turbines and to the time for repairing.

The third source of risk considered here is the correlation between wind turbines energy production. Indeed, since in a wind farm many turbines act together, it would be better to consider

* Corresponding author.
E-mail address: fpetroni@unica.it (F. Petroni).

http://dx.doi.org/10.1016/j.jweia.2015.06.018
0167-6105/

their multivariate distribution of energy production instead of considering the turbines as independent and with an identical production of energy. This risk factor is considered through Copulas that permit the construction of a multivariate model having fixed marginals (univariate) distributions.

In the present work we consider a wind speed database of a specific site in Alaska and we assume to put there a wind farm composed of 10 commercial wind turbines. We propose then a procedure to estimate correctly the energy production of the allocated wind farm by taking into account the three sources of uncertainty.

The paper is organized as follows: in Section 2 we describe the wind speed database and the commercial wind turbines considered in the application. In Section 3 we present the models at the basis of the proposed procedure. Section 4 shows the application of the procedure to our database, sensitivity analysis and the comparison with the energy estimation of a wind farm without considering the aforementioned risk factors. At last, in Section 5 we give some concluding remarks.

2. Data and technology used

2.1. Database

The database of wind speed used in our analysis was collected by the National Data Buoy Center (www.ndbc.noaa.gov). Particularly, we downloaded the data from the inshore station RDDA2 that is situated at 67.577°N 164.065°W in Alaska. The data are available for six years ranging from 2006 to 2012 with a sample period of six minutes. The instrumentation is located at 10 m above the ground and mean and maximum values of wind speed in the database are, respectively, of 4.5 and 34.8 m/s.

This database is used to analyze the production of energy from commercial wind turbines which have the hub at a given altitude. Then, since the altitude from the ground influences the wind speed, we have to transform the 10 m velocities to corresponding data at the required altitude. It is well known in the literature that wind speed has the following dependence from the altitude (see e.g. D'Amico et al., 2013b):

$$v_h = v_{rif}\left(\frac{h}{h_{rif}}\right)^{\alpha}, \qquad \alpha = \frac{1}{\ln\dfrac{h}{z_0}} \tag{1}$$

where v_h is the wind speed at the height of the wind turbine hub, v_{rif} is the value of the wind speed at the height of the instrument, h and h_{rif} are the height of the wind turbine and of the instrument ($h = 50$ m and $h_{rif} = 10$ m), respectively. The parameter z_0 is a factor that takes into account the morphology of the area near the wind turbine. For a region without buildings or trees, this parameter varies from 0.01 to 0.001, instead for the offshore application it is equal to 0.0001. In our analysis we consider a mean value for an onshore application, then we fix z_0=0.005. With this transformation we have an increase of the mean and also of the maximum value of the wind speed, which became 5.4 and 42 m/s, respectively. In Fig. 1 we show the main characteristics of the database. In panel (a) we show the probability density function (PDF) of the wind speed. Panel (b) shows a piece of one year of the time series, instead in panel (c) we report the Box-Plot where we can see that the median wind speed is below the mean value and that in the fourth quartile there are all the wind speeds greater than 15 m/s.

2.2. Commercial wind turbine

Wind turbines convert the kinetic energy of wind into electrical power. The quantity of converted energy depends, *ceteris paribus*, on the installed wind turbines. In this application we chose a commercial wind turbine, the 330 kW Enercon E33. This turbine has a height of the hub from the ground of 50 m. The most important property of each wind turbine is its power curve that characterizes the performance of the wind turbine. This curve gives the energy produced by the turbine as a function of wind speed. The power curve of the 330 kW Enercon E33 is represented in Fig. 2 and the numerical values are reported in Table 1. For the present application we converted each wind speed data into energy by using the power curve in Fig. 2. The power curve is given by the producer only as discrete points (see Table 1) while wind speed is measured continuously, then, a linear interpolation between subsequent discrete states of the power curve was

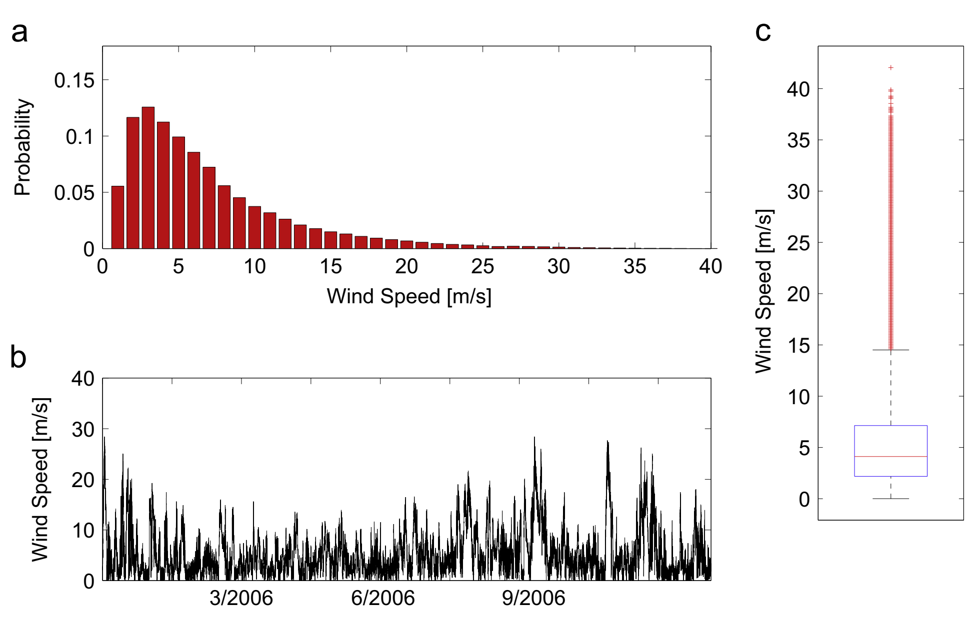

Fig. 1. Wind speed data of the RDDA2 station. (a) Histogram of the probability density function, (b) one year time series, and (c) Box-Plot.