Electric Power Systems Research 141 (2016) 549–561

Contents lists available at ScienceDirect

Electric Power Systems Research

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

Inverse Burr distribution for extreme wind speed prediction: Genesis, identification and estimation

Elio Chiodo, Pasquale De Falco*

Department of Electrical Engineering and Information Technology, University of Naples Federico II, Via Claudio, 21, 80125 Naples, Italy

ARTICLE INFO

Article history:
Received 20 January 2016
Received in revised form 23 July 2016
Accepted 28 August 2016

Keywords:
Wind power plants
Extreme values
Wind speed
Inverse Burr distribution

ABSTRACT

The randomness of the wind source is a concerning issue for managing power plants in reliable conditions. High values of wind speed are undesirable since wind farms provide zero power for values greater than their cut-off thresholds. Also, the mechanical safety of the installations can be seriously compromised by extreme values of wind speed. Therefore, a reliable estimation of extreme values of wind speed is mandatory. An Inverse Burr distribution is proposed as an useful alternative for the probabilistic modeling of extreme values of wind speed. Distribution parameters were estimated through maximum likelihood and moment estimation procedures, and through a new proposal, the quantile estimation procedure. The proposed model is validated on several real wind datasets, comparing the proposed model with commonly-used extreme value models. Numerical applications showed that the proposed model is a valid and feasible alternative to the classical extreme value distributions for extreme values of wind speed.

1. Introduction

Wind power production significantly increased in recent years due to environmental, technological, and economic benefits [1,2]. However, the power output of a wind generator strongly varies as the speed of the wind energy source varies; wind speed (WS) is intrinsically a random variable (RV), since it depends on many meteorological and orographic factors [3,4], and therefore the corresponding wind power is also a RV. The high penetration of unpredictable, intermittent power sources in electrical networks is a concerning issue in the optimal management of power networks [5,6], since many technical considerations (such as network frequency regulation, grid energy balancing and power quality assessment) must be addressed. In order to mitigate such kind of issues, accurate wind power forecasting tools are needed; in particular, reliable predictions of wind power could be useful in many transmission system operations, such as unit commitment and provision of ancillary services [7].

The randomness of WS also has a great impact on the mechanical reliability of wind power systems, since extreme values of wind speed (EWS) may damage sensible components of the structures, such as towers and wind blades [8,9]. Wind turbine design has recently exploited developments from aerospace and material engineering and nuclear industry, in order to increase safety and reliability levels [10,11]; however, local and national authorities usually ask more and more for an evaluation of the safety and risks of industrial activities, and this also holds for the siting of new wind farms, as part of required reports on the related environmental impact. In particular, the fatigue failure of the tower is a concerning issue, and the stochastic nature of EWS is usually used as input in mechanical analysis [10].

Furthermore, values of WS that are greater than the “cut-off” value of the wind generator are generally undesirable, since the electric generator has to be disconnected from the wind turbine not to compromise the electrical section of the wind power system; consequently, the “cut off” value of the generator must be chosen according to the characterization of EWS in the particular location, since it has a great impact on aggregate power production [9,11–14].

Then, considering both the disadvantages (no power output and mechanical stress on the structures), the statistical characterization and prediction of EWS is mandatory in the decision-making process when evaluating yearly output production for the wind power system design [13], and also in real-time operating conditions in order to implement some measures to reduce the corresponding drawbacks.

* Corresponding author.
E-mail addresses: chiodo@unina.it (E. Chiodo), pasquale.defalco2@unina.it (P. De Falco).

http://dx.doi.org/10.1016/j.epsr.2016.08.028
0378-7796/

In relevant literature, many studies have dealt with the proposal of accurate deterministic and probabilistic WS and EWS forecasting tools [15–21]; as pointed out in Ref. [5], probabilistic WS forecasts can provide additional information concerning wind uncertainty for economic operation and competitive trading, and therefore are way more efficient than traditional, deterministic forecasts.

Motivated by these issues, this paper mainly focuses on probabilistic EWS characterization for a proper understanding of destructive wind forces, which may affect mechanical safety and reliability of wind power systems; an estimation of EWS is therefore proposed through statistical procedures [22,23] based on "classical" maximum likelihood estimation (MLE) and moment estimation (ME), and through a new proposal, the quantile estimation (QE) which is sometimes easier to evaluate, implying in particular cases a simple algebraic computation, while MLE and ME methods show in some cases convergence issues.

The EWS characterization is based upon a suitable Inverse Burr distribution, which is typically used in extreme values studies [24,25], but has never been used before for EWS. Indeed, many works have dealt with the determination of the best probability models for a proper characterization of WS randomness, as discussed in Section 2. The choice of an incorrect model may lead to significant errors, especially in the estimation of upper and lower WS quantiles or EWS quantiles. This may of course affect the evaluation of mechanical reliability of wind power structures, which is the primary concern of this paper. Moreover, accurate wind speed modeling is the first step to also achieve accurate wind energy production estimation, since significant biases may result from assuming an incorrect model. The impact of these errors is even more concerning when upper and lower WS quantiles are to be transformed into the corresponding quantiles of the wind power density, since they are usually obtained through a cubic rule.

Therefore, the Inverse Burr distribution is compared to some different distributions that have been widely acknowledged as suitable EWS distributions, such as the Gumbel distribution and the Inverse Weibull distribution [26].

The paper is organized as follows. Section 2 provides a brief recall of commonly-used wind speed distributions, while Section 3 shows the selected distributions used to model EWS and the Inverse Burr proposal. Section 4 gives some hints on the Inverse Burr estimation and identification. Section 5 shows the results of our numerical applications to validate the proposed model, and our conclusions are shown in Section 6. A list of symbols and acronyms is provided in Appendix A.

2. Selected probability distributions for wind speed stochastic characterization

The probabilistic characterization of WS and EWS is a challenging task in wind power production assessment, mechanical safety, reliability and for wind gust prediction [27–30]. Also, once the distribution has been selected for the particular application, the estimation of the corresponding parameters is not exempt from issues. Robustness is the main requirement of an estimation method, in order to provide accurate estimates in different conditions; indeed, in many applications, distribution parameters quickly vary as some external factors (i.e., atmospheric conditions) vary, and therefore a robust estimation prevents the parameters from being widely over-estimated or under-estimated.

In the following, two of the most common WS distributions are briefly presented and discussed.

2.1. Weibull distribution

The Weibull distribution is the most used probability density function (PDF), since it usually fits the majority of observed WS data [26,31–33]. The analytic expressions of Weibull PDF and cumulative density function (CDF) for a non-negative RV x are, respectively:

$$f(x|\alpha,\beta) = \frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1} e^{-\left(\frac{x}{\alpha}\right)^{\beta}} \tag{1}$$

$$F(x|\alpha,\beta) = 1 - e^{-\left(\frac{x}{\alpha}\right)^{\beta}} \tag{2}$$

where α, β are the scale parameter and the shape parameter, respectively, both defined as positive numbers. Equivalent forms of Eqs. (1) and (2) can be provided by denoting $\lambda = \frac{1}{\alpha^{\beta}}$:

$$f(x|\lambda,\beta) = \beta\lambda x^{\beta-1} e^{-\lambda x^{\beta}} \tag{3}$$

$$F(x|\lambda,\beta) = 1 - e^{-\lambda x^{\beta}} \tag{4}$$

The median value of Weibull distribution is:

$$m = \alpha(\log 2)^{\frac{1}{\beta}} = \frac{1}{\sqrt[\beta]{\lambda}}(\log 2)^{\frac{1}{\beta}} \tag{5}$$

When Eqs. (1) or (3) are used to model WS, the scale parameter β can usually be considered as a given number, since it is strongly correlated to the geographic location and, therefore, it can be assumed as a known constant for a given site [32,33]. In particular, for $\beta = 2$ the Weibull distribution falls into the well-known Rayleigh distribution. Therefore, a Weibull distribution with constant shape parameter $\beta = 2$ is implicitly assumed by selecting a Rayleigh distribution as a suitable model for WS (e.g., in Ref. [33]). Parameter α (or λ alternatively) varies instead as the meteorological conditions vary, and therefore its estimation is way more challenging.

Weibull distribution proved its suitability in different conditions for a rough characterization of WS; however, it does not perform well for EWS, since lower tail usually does not fit well, and therefore upper quantiles could be severely underestimated or overestimated [28,29,34]. Also, this problem is way more challenging if the size of the available dataset of WS measurements is not particularly large; in fact, EWS are not so frequent, and therefore it is not common to find sufficient samples for an accurate estimation of upper quantiles. Then, other distributions were proposed to cope with this problem.

2.2. Burr distribution

Burr distribution [26,28,29] is often selected in WS applications. Burr distribution was obtained in Ref. [33] from a mixture of Weibull distributions, considering a parameterization of several related meteorological variables, such as temperature and pressure. The variations of these external variables have a great impact on the parameter λ in Eq. (3), as said before. Then, let's consider the shape parameter β as a constant and the parameter λ as a RV Λ, modeled in a Bayesian approach [35,36] through a Gamma PDF:

$$g(\lambda|\delta,\xi) = \frac{\xi^{\delta}\lambda^{\delta-1}}{\Gamma(\delta)} e^{-\xi\lambda} \tag{6}$$

where ξ is the rate parameter and δ is the shape parameter, both defined as positive numbers, and $\Gamma(\cdot)$ is the Gamma function.

Using the total probability theorem, the unconditional CDF can be expressed as:

$$F(x) = 1 - \int_{0}^{+\infty} g(\lambda) e^{-\lambda x^{\beta}} d\lambda \tag{7}$$