Energy Conversion and Management 149 (2017) 303–317

Contents lists available at ScienceDirect

Energy Conversion and Management

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

Development of a statistical bivariate wind speed-wind shear model (WSWS) to quantify the height-dependent wind resource

Christopher Jung *, Dirk Schindler

Environmental Meteorology, Albert-Ludwigs-University of Freiburg, Werthmannstrasse 10, D-79085 Freiburg, Germany

ARTICLE INFO

Article history:
Received 26 May 2017
Received in revised form 6 July 2017
Accepted 15 July 2017

Keywords:
Wind energy
Power law
Copulas
Johnson SB distribution
Dagum distribution
Germany

ABSTRACT

The goal of this study was to develop a statistical bivariate wind speed-wind shear model (WSWS). The development of WSWS is based on near surface wind speed data available from 397 measurement stations distributed over Germany, as well as on ERA-Interim reanalysis wind speed data available in 1000 m above ground level (a.g.l.). These data were used (1) to calculate empirical distributions of wind speed in 1000 m a.g.l., (2) empirical distributions of the wind shear exponent, and (3) to fit theoretical distributions to the empirical wind speed and wind shear exponent distributions. It was found that the four parameter Johnson SB distribution reproduces the shape of the wind speed in 1000 m a.g.l. empirical distributions best. The four parameter Dagum distribution provided good fits to the empirical wind shear distributions. The parameterized wind speed and wind shear marginal distributions were then linked by 16 joint copulas. Goodness-of-fit evaluation of the joint copulas demonstrates that the Gaussian-Gaussian copula reproduces the empirical bivariate wind speed-wind shear distribution most accurately. By using WSWS it is possible to continuously calculate the wind speed probability density function in hub heights between 10 m a.g.l. and 200 m a.g.l. This allows WSWS to be applied to virtually any power curve for computing the wind energy yield and capacity factor in the analyzed hub height range. A one-time site-specific parametrization of WSWS is sufficient for a comprehensive height-dependent exploitation of the available wind resource.

1. Introduction

The current global electricity consumption is mainly covered by conventional fuels [1]. However, it is essential to find appropriate substitutes for conventional fuels. First, their utilization is strongly connected with greenhouse gas emissions, which cause climate change [2]. Second, emission of air pollutants by combustion processes can impair human health [3]. Moreover, the peaking of fossil fuels is anticipated in the next decades [4]. It is expected that wind energy will be one important substituent for conventional fuels and plays a major role in the future energy mix [2].

Wind turbines are used to convert the kinetic energy of the airflow first into mechanical and then into useful electric energy [5]. The countries with largest installed wind energy capacity in 2016 were China (168,690 MW), the USA (82,184 MW) and Germany (50,018 MW) [6]. From these three countries Germany has by far the highest wind turbine density with 0.076 wind turbines/km^2 and an average capacity of ~1.68 MW per onshore wind turbine. At the end of 2016, a total of 27,270 onshore and 947 offshore wind turbines were installed in Germany [7] and the share of renewable energies in the electricity consumption was 31.7% corresponding to a gross electricity production of about 188 billion kWh [8]. In the same year, wind energy covered 13.0% of Germany's gross electricity consumption. According to the German Renewable Energies Act in the version issued 2014, Germany aims to further increase the share of renewable energies until 2025 to 40–45% and until 2035 to 55–60%. To achieve these goals, a massive installation of new wind turbines is necessary.

Prior to installation of wind turbines accurate wind resource assessment is necessary [9–11]. Wind resource assessment can be carried out by connecting wind speed (x) and characteristics of the land surfaces [12]. Often, the wind power density function is used as an important indicator for the available wind resource [13]. It is estimated by

$$P(x) = \frac{1}{2}\rho x^3 f(x) \quad (1)$$

where ρ is the air density. Accordingly, P increases with the cube of x, which means that a rather small error in the assessment of x leads to a large estimation error of the available wind resource. The mean wind power density ($\bar{P}$) is often used as a qualitative magnitude to

* Corresponding author.
E-mail address: christopher.jung@mail.unr.uni-freiburg.de (C. Jung).

http://dx.doi.org/10.1016/j.enconman.2017.07.033

Nomenclature

Acronyms

a.g.l.	above ground level
a.s.l.	above sea level
B	three parameter Burr distribution
B4	four parameter Burr distribution
BB	seven parameter Burr-Burr distribution
BD	seven parameter Burr-Dagum distribution
BG	six parameter Burr-Gamma distribution
BGEV	seven parameter Burr-Generalized Extreme Value distribution
BN	six parameter Burr-Normal distribution
BW	six parameter Burr-Weibull distribution
C1	case one: $x_{1000\text{m}} \leq 9.0$ m/s
C2	case two: $x_{1000\text{m}} > 9.0$ m/s
CC	Clayton-Clayton copula
cdf	cumulative distribution function
CF	Clayton-Frank copula
CG	Clayton-Gaussian copula
CGu	Clayton-Gumbel copula
D	four parameter Dagum distribution
D3	three parameter Dagum distribution
DD	seven parameter Dagum-Dagum distribution
DG	six parameter Dagum-Gamma distribution
DGEV	seven parameter Dagum-Generalized Extreme Value distribution
DN	six parameter Dagum-Normal distribution
DW	six parameter Dagum-Weibull distribution
ecdf	empirical cumulative distribution function
epdf	empirical probability density function
FC	Frank-Clayton copula
FF	Frank-Frank copula
FG	Frank-Gaussian copula
FGu	Frank-Gumbel copula
G	two parameter Gamma distribution
G3	three parameter Gamma distribution
GC	Gaussian-Clayton copula
GEV	three parameter Generalized Extreme Value distribution
GEVG	six parameter Generalized Extreme Value-Gamma distribution
GEVGEV	seven parameter Generalized Extreme Value-Generalized Extreme Value distribution
GEVN	six parameter Generalized Extreme Value-Normal distribution
GEVW	six parameter Generalized Extreme Value-Weibull distribution
GF	Gaussian-Frank copula
GG	Gaussian-Gaussian copula
GG5	five parameter Gamma-Gamma distribution
GGu	Gaussian-Gumbel copula
GN	five parameter Gamma-Normal distribution
Gu	two parameter Gumbel distribution
GuC	Gumbel-Clayton copula
GuF	Gumbel-Frank copula
GuG	Gumbel-Gaussian copula
GuGu	Gumbel-Gumbel copula
GW	five parameter Gamma-Weibull distribution
hhr	hub height range (m)
JSB	four parameter Johnson SB distribution
JSU	four parameter Johnson SU distribution
K	four parameter Kappa distribution
LMOM	L-moment method
LSE	least squares estimation method
MLE	maximum likelihood estimation method
MOM	moment method
N	two parameter truncated Normal distribution
NN	five parameter Normal-Normal distribution
No	two parameter Normal distribution
NW	five parameter Normal-Weibull distribution
pch	combination of power curve and hub height
pdf	probability density function
PEM	parameter estimation method
Ray	one parameter Rayleigh distribution
Ray2	two parameter Rayleigh distribution
S	abbreviation
W	two parameter Weibull distribution
W3	three parameter Weibull distribution
Wak	five parameter Wakeby distribution
WSWS	wind speed-wind shear model
WW	five parameter Weibull-Weibull distribution

Symbols

Φ	cumulative distribution function of standard normal distribution
$\bar{P}_W$	average wind turbine power output (W)
$\tilde{R}^2$	median of coefficient of determination
φ_d	cumulative distribution function of a multivariate normal distribution
$\widetilde{AEY}$	median annual average wind energy yield over all combinations of power curve and hub height (GWh/yr)
$\tilde{E}$	median power law exponent
$\bar{F}$	mean of empirical cumulative distribution function values
$\hat{F}$	estimated cumulative distribution function
$\widetilde{M'}$	median of the comprehensive goodness-of-fit metric
$\widetilde{MPA}$	median of percentage error of the mean of the cubes of wind speed (%)
M^{max}	maximum of GoF-metric
M^{min}	minimum of GoF-metric
$\bar{P}$	average wind power density (W/m^2)
$\bar{X}$	mean of the variable X
$\hat{X}$	estimated value of the variable X
$\widetilde{cf}$	median capacity factor over all combinations of power curve and hub height
$\bar{x}$	average of daily mean wind speed in the investigation period (m/s)
$\tilde{x}$	median wind speed (m/s)
$\sum$	covariance matrix
AEY	annual average wind energy yield (GWh/yr)
c	Gaussian copula
cf	capacity factor
E	power law exponent
f	probability density function
F	cumulative distribution function
h	height a.g.l. (m)
ho	number of hours in a year
k	kth case
M	goodness-of-fit metric
M'	comprehensive goodness-of-fit metric
MPA	percentage error of the mean of the cubes of wind speed (%)
n	sample size
nn	number of goodness-of-metrics
NP	number of parameters
o	marginal distribution
P	wind power density (W/m^2)