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Copula-based estimation of directional wind energy yield: A case study from Germany

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ABSTRACT

The mixed Burr-Generalized Extreme Value distribution (BGEV) and Gaussian copulas were used in a two-step procedure for estimating the directional wind energy yield in 100 m above ground level in Germany. In a first step, BGEV was fitted to the marginal distributions of ERA-5 reanalysis horizontal wind vector component data available from the European Centre for Medium-Range Weather Forecasts. Then, Gaussian copulas were fitted to the bivariate distributions of the wind vector components. It is demonstrated that the combination of BGEV and Gaussian copulas allows a very accurate simulation of the directional wind energy yield. Results from goodness-of-fit evaluation indicate very good fit to virtually all wind speed-wind direction regimes reproduced by the ERA-5 data in the period 2010–2016. The directional mean annual wind energy yield was simulated for eight wind direction sectors by applying a 3.05 MW wind turbine power curve. The simulation results illustrate that Germany's available wind energy is highly dependent on the wind direction. Mainly southwestern and western flows contribute to the total mean annual wind energy yield. All other wind direction sectors contribute only to a minor extend to the amount of extractable wind energy. The areas where mean annual wind energy yield is highest are mostly located in Northern Germany at the North Sea and Baltic Sea coasts.

1. Introduction

In regions with one or more prevailing wind directions, wind resource assessment is challenging. This is because the available wind resource varies as a function of the wind direction [1]. Therefore, it is important to combine knowledge on empirical wind speed distributions with information on empirical wind direction distributions [2].

The importance of including wind direction into wind resource assessment has been emphasized in a number of previous studies. The performance of wind turbines [3], clusters of wind turbines and wind farms is wind direction-dependent [4]. Small variations in the wind direction may considerably change the power output of wind farms [5]. The directional wind energy yield is an important factor for wind farm radius and turbine distance constraints [6].

To maximize the total energy yield, the optimization of the micro-siting of wind turbines being part of wind farms is indispensable [7]. This is especially true when wind farms are located in complex terrain [8]. Then, an optimized alignment improves wind turbine performance and minimizes wake effects [9]. On the other hand, misalignment of wind turbines induces wake effects, which result in a decreasing performance and power output [10].

The consideration of both wind speed and wind direction allows for quantifying the variation of the harvesting direction for wind turbines so that their efficiency can be maximized and costs can be reduced [11]. It has been demonstrated that accurate wind direction tracking maximizes wind power extraction [12]. The accuracy of simulations of wind turbine wake-induced power losses improves when wind direction is taken into account [13]. Moreover, including wind direction into wind resource assessment improves wind turbine performance predictions [14].

Not only on small spatial scales information about the variability of wind direction is important. Comprehensive knowledge of wind direction distributions also helps estimating and maximizing the directional wind energy yield on larger spatial scales such as the national scale. As inherent part of the long-term wind climate, wind direction is a critical issue in the selection process of candidate areas for wind farms [15]. Since the aggregate generation of wind farms also depends on the wind direction, the inclusion of wind direction into statistical wind resource models enables a more detailed analysis of large-scale wind power generation [16]. Furthermore, consideration of the directional wind energy yield helps improving national wind turbine installation scenarios and contributes to increasing the efficiency of future wind energy expansion [17].

Up to now, the wind energy potential was often assessed without

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Nomenclature

Acronyms

a.g.l.	above ground level
B	Burr distribution
BGEV	mixed Burr-Generalized Extreme Value distribution
C	Gaussian copula
cdf	cumulative distribution function
E	east
ecdf	empirical cumulative distribution function
ECMWF	European Center for Medium-Range Weather Forecasts
ERA-5	reanalysis data
GC	grid cell
GEV	Generalized Extreme Value distribution
GoF	goodness-of-fit
I	identity matrix
N	north
NE	northeast
NW	northwest
PP	probability plot
Q	quadrant
S	south
SE	southeast
SW	southwest
T	transpose of a matrix
W	west

Symbols

AEY	annual wind energy yield (GWh/yr)
$\overline{AEY}$	mean annual wind energy yield (GWh/yr)
cc	two-dimensional correlation coefficient
d	number of marginal distributions
D	wind direction (°)
f	probability density function
F	cumulative distribution function
MAE	mean absolute error (m/s)
n	time series length
$P(U)$	wind turbine power curve (MW)
$\overline{P}$	mean wind turbine power output (kW)
R^2	coefficient of determination
u	zonal (west-east) wind vector component (m/s)
U	wind speed (m/s)
v	meridional (north-south) wind vector component (m/s)
x	arbitrary variable
y	arbitrary variable
β	shape parameter of Burr distribution
η	scale parameter of Generalized Extreme Value distribution
ι	shape parameter of Generalized Extreme Value distribution
μ	location parameter of Generalized Extreme Value distribution
o	marginal distribution
π	pi
σ	scale parameter of Burr distribution
Σ	covariance matrix
φ	multivariate normal distribution
Φ	cumulative distribution of the standard normal distribution
ψ	shape parameter of Burr distribution
ω	mixing parameter

Subscripts

B	Burr distribution
$BGEV$	mixed Burr-Generalized Extreme Value distribution
C	Gaussian copula
d	number of marginal distributions
E	east
GEV	Generalized Extreme Value distribution
i	counter
j	counter
mod	modeled
N	north
NE	northeast
NW	northwest
PP	probability-probability plot
S	south
SE	southeast
SW	southwest
u	zonal (west-east) wind vector component
v	meridional (north-south) wind vector component
W	west

considering the influence of the wind direction on total wind energy yield. This might be due to limited availability of wind direction distributions or difficulties arising from fitting wind direction distributions. In contrast to wind speed, wind direction varies on a circular scale between 1° and 360°. This kind of variability requires the use of distributions whose probability density functions account for the circular behavior of wind direction [18]. Therefore, the van Mises distribution and mixtures of the van Mises distribution, which allow fitting distributions of circular variables, were used in wind energy applications [19]. The directional wind resource at individual sites was also assessed by bivariate Farlie-Gumbel-Morgenstern copulas combining information on wind speed and wind direction distributions [11]. Furthermore, the Johnson-Wehrly model, Farlie-Gumbel-Morgenstern copulas and Plackett copulas were tested for their suitability for reproducing bivariate distributions of wind speed and wind direction at individual sites [15]. In a recent study focusing on wake effects on the power output of wind farms, Frank copulas were used for describing the dependence between wind speed and wind direction [20].

It is clear from the available studies that the wind energy yield strongly depends on the wind direction. Therefore, this study introduces a parsimonious methodology that directly fits bivariate wind vector component distributions. In an earlier study [21], it was noted that the directional wind energy yield should be estimated based on the wind vector components to maintain the statistical dependence between wind speed and wind direction. Here, the wind vector component-based approach is taken up again and further developed. The further development allows its accurate application to virtually all wind regimes in Germany present in the latest version of the European Center for Medium-Range Weather Forecasts (ECMWF) reanalysis data (ERA-5). It is demonstrated and evaluated that the methodology is well suitable for assessing the multi-annual directional wind energy yield in Germany in the period 2010–2016.

2. Methodology

The assessment of directional wind energy yield introduced in this study includes the following steps (Fig. 1): (1) obtaining hourly ERA-5 zonal (u) and meridional (v) wind vector component data for Germany