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On the selection of bivariate parametric models for wind data

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HIGHLIGHTS

- Analytic description of univariate distributions of wind speed and wind direction.
- Implementation of three bivariate parametric distributions at six locations.
- Analytic evaluation of the adopted bivariate models based on seven metrics.
- Johnson-Wehrly model provides better fits than two copula families.
- The best bivariate model is applied in wind energy assessment.

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ABSTRACT

The joint modelling of wind speed and direction in an area is important for wind energy projects and a variety of ocean engineering applications. In the context of wind resource assessment, the analytical description of wind climate is usually confined to the description of wind speed; however, the accurate joint description of the directional and linear wind characteristics is also essential at the candidate sites for wind farm development. In this work, three families of models for the joint probabilistic description of wind speed and wind direction are examined and thoroughly evaluated, namely Johnson-Wehrly and two families of copulas, Farlie-Gumbel-Morgenstern and Plackett families. These models are applied on long-term wind data obtained by different measuring devices (five oceanographic buoys and one meteorological mast) for six different locations of the Greek and Spanish waters in the Mediterranean Sea. The proposed bivariate models are theoretically sound and tractable, since they are defined by closed relations and are constructed by considering the marginal (univariate) distributions of wind speed and wind direction along with an appropriate dependence structure of the involved variables. In the univariate case, wind speed modelling is based on a wide range of conventional and mixture distributions, while wind direction is modelled through finite mixtures of von Mises distributions. The evaluation of the bivariate models is based on seven bin-specific goodness-of-fit criteria, namely root mean square error, relative root mean square error, mean absolute error, index of agreement, chi-square statistic, adjusted coefficient of determination and normalized deviation. The obtained results suggest that the performance of the Johnson-Wehrly model is rather superior, since it provides better fits compared to the other two families of bivariate distributions for the overwhelming majority of the examined cases and criteria. The most efficient bivariate models are then implemented to estimate the detailed structure of wind power density at three selected locations.

1. Introduction

Exploitation of marine winds has long been recognized as one of the key aspects among renewable energy sources for reducing carbon emissions and securing energy supply across Europe. Among the European countries, the UK and Germany hold the leading position for offshore wind farm (OWF) development, while recent studies have highlighted that the Mediterranean waters are also suitable for initiating such investments [1–4]. For instance, taking into consideration strictly technical criteria examined during the planning phase of an OWF, i.e. the available wind resource (including estimation of variability and quantification of uncertainties), bottom topography and geomorphology, distance to shore, and proximity to large ports and power grid connections, Greece is at

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Nomenclature

English letters

d_{ij}	normalized deviation
$F_X(x)$	cumulative distribution function of the random variable X
$f_X(x)$	probability density function of the random variable X
$F_{X,A}(x,\alpha)$	joint (bivariate) cumulative distribution function of the random variables X, A
$f_{X,A}(x,\alpha)$	joint (bivariate) probability density function of the random variables X, A
$\tilde{F}_X$	estimate of F_X obtained from a fitted analytic model
I_0	modified Bessel function of the first kind and zero order
n	sample size
N	total number of non-empty bins
N_T	total number of bins
p	probability/observed frequency
$R^2_{a,1}$	coefficient of determination for the univariate case
$R^2_{a,2}$	coefficient of determination for the bivariate case
$r_{U\Theta}$	statistical association between wind speed U and wind direction Θ
SRS_E	sum of relative squared error
SS_E	sum of squared error
SS_T	total sum of squares
U	wind speed (random variable)
X	linear random variable
$x(F_X)$	quantile function of the random variable X (inverse cumulative distribution function)

Greek letters

A	angular random variable
Θ	wind direction (random variable)
ψ	variable defined through the cumulative distribution functions of the linear and directional variable in the Johnson-Wehrly model
χ^2	chi square test or chi square statistic
ψ_P	"correlation-type" parameter for the Plackett family of distributions

Abbreviations

A-D	Anderson-Darling (goodness-of-fit test)
BET	Beta (distribution function)
BIC	Bayesian information criterion
BUR	Burr (distribution function)
cdf(s)	cumulative distribution function(s)
DAG	Dagum (distribution function)
ERL	Erlang (distribution function)
FAL	Fatigue Life (distribution function)
FGM	Farlie-Gumbel- Morgenstern
GAM	Gamma (distribution function)
GEV	generalized Extreme Value (distribution function)
GNG	generalized Gamma (distribution function)
GNL	generalized logistic (distribution function)
GPA	generalized Pareto (distribution function)
IA	index of agreement
JSB	Johnson S_B (distribution function)
JW	Johnson-Wehrly
K-S	Kolmogorov-Smirnov (goodness-of-fit test)
KAP	Kappa (distribution function)
KUM	Kumaraswamy (distribution function)
LGL	Log-Logistic (distribution function)
LGN	Lognormal (distribution function)
LP3	Log-Pearson 3 (distribution function)
MAE	mean absolute error
NAK	Nakagami (distribution function)
NN	mixture of truncated (from below) normal distribution functions
OWF	offshore wind farm
pdf(s)	probability density function(s)
PE6	Pearson 6 (distribution function)
PER	Pert (distribution function)
RAY	Rayleigh (distribution function)
RMSE	root mean square error
RRMSE	relative root mean square error
vM	von Mises (distribution function)
WAK	Wakeby (distribution function)
WEI	Weibull (distribution function)
WGEV	mixture of Weibull and Generalized Extreme Value distribution functions
WW	mixture of two Weibull distribution functions

the top four European Mediterranean countries regarding favourable sites for OWF development; see Soukissian et al. [5].

The analytic knowledge and modelling of wind climate in a candidate area is a critical issue in wind energy assessment in order to optimize the layout of a wind farm, improve system efficiency, estimate accurately wind energy potential and reduce costs. Apart from wind speed, the importance of including in relevant analyses wind direction as well has been highlighted in many studies; see, for example, Porté-Agel et al. [6], Herbert-Acero et al. [7], Waewsak et al. [8], Zhang [9], Song et al. [10]. Specifically, in the study of Porté-Agel et al. [6], the impacts of relatively small changes in wind direction are examined with respect to the effects on wakes and total power generation, while in Song et al. [10], the fluctuation of power generation is quantitatively evaluated under varying wind directions. In the monograph of Zhang [9], the effects of wind direction on the evaluation of the offshore wind resource, the micro-sitting procedure and the optimization of the offshore turbine layout of an OWF are described in detail. In Herbert-Acero et al. [7], a review of the methods as regards the design and optimization of wind farms is presented. It is emphasized that the wind farm planning process is primarily based on the numerical convolution of the output wind field (obtained from micro-scale flow models) with the probability distribution of wind speed and direction in order to obtain the average wind resource maps at a specific area. Regarding the optimization of the wind farm layout, the reduction of power losses due to the operation of wind turbines in wakes of other turbines is a priority. These losses may be important and dependent, apart from the distance between the turbines, on the wind direction, the intensity of the turbulence and the particular turbine type. A detailed description of wind direction in the design of the wind farm layout in order to maximize wind energy capture is presented in Kusiak and Song [11]; see also Emami and Noghreh [12], Chowdhury et al. [13].

From a stochastic modelling point of view, wind speed and direction are treated as dependent random variables that exhibit variations both in the spatial (e.g. from site to site, height of measurements, etc.) and the temporal domain (e.g. from year to year, within each year, etc.); for this reason, they should be thoroughly examined based on long-term wind data. Regarding wind speed, in addition to the estimation of the standard low-order statistical