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Simulation of non-stationary wind speed and direction time series

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ABSTRACT

The simulation of synthetic wind time series is strictly necessary, among others, to assess the risk of structures and systems, to model the dynamic of morphological features like dunes, or to investigate the potential of wind energy in a certain location. For all these applications, a tool able to simulate time series of wind speed and direction is required. In this paper we propose a methodology for the simulation of bivariate non-stationary time series of wind speed and direction. This methodology takes into account the circular nature of the wind direction, as well as the mean annual cycle of both wind speed and direction. For modelling the joint distribution of the two variables, wind speed is modelled conditioned to the wind direction. For modelling short-term self- and cross-dependency among the variables a Vector Autoregressive (VAR) model of order p is used, with an innovation process at time t that depends on the value taken by the variables at time $t-1$, based on the use of a mixture of multivariate normal distributions. The proposed methodology is applied to a case study, simulating several synthetic series, of the same length as the original series. The simulated series satisfactorily captures the characteristics of averaging or common data (i.e. with low or moderate speed) and, under certain independence conditions, the directional extreme value distribution of the wind speed is also properly reproduced.

1. Introduction

The simulation of wind time series is a useful tool in several engineering branches, as fatigue analysis, wind energy exploitation studies, plume simulation of atmospheric pollutants, etc. In some cases, it is only required to simulate wind speed time series, usually looking for the simulated series to reproduce as accurately as possible the behaviour of the original series for both central and extreme values of the variable (e.g. Torrielli et al., 2011, 2013, 2014).

However, accurate modelling of wind directions is as important as accurate modelling of wind speeds when it comes to analysing the reliability and operability of structures or systems where the direction of attack of the wind determines the pressures and/or the wind-induced vibrations. While in many applications it is sufficient to only simulate wind speeds, in those applications where both wind speed and direction are required, previously proposed methodologies (see e.g. Shamshad et al., 2005; Morales et al., 2010 or Torrielli et al., 2011, 2014) will be of limited applicability, being necessary to develop simulation methodologies that address the dependency between wind speed and direction.

Some researchers have dealt with wind directions by means of Markov chain models. Youcef Ettoumi et al. (2003) used a first-order Markov chain model with nine states for representing the nine directions of the compass card. They found that the first-order Markov chain model fits well to the wind-direction data. In addition, they provided a combination of a first-order, nine-state Markov chain model for the wind direction with a first-order, three-state Markov chain model for the wind speed, and their final results were found to yield a good representation of the observed wind data. Masseran (2015) applied a Markov chain model for describing stochastic and probabilistic behaviour of wind direction data, toward aiding the process of energy assessment. However, his plot of time series data indicates that some trend in the observed states cannot be captured by a first-order Markov chain model.

From other previously proposed simulation methods that do take account of wind direction, some do not consider the circular behaviour of this variable (i.e. wind direction is modelled as it were a linear variable) nor its non-stationarity (e.g. Solari and van Gelder, 2012) or, when do take account of these issues (e.g. Solari and Losada, 2014), they fail to reproduce the joint distribution of wind speed and direction.

In this paper we propose a new methodology for the simulation of bivariate non-stationary time series (i.e. bivariate random process) of wind speed and direction, which takes into account the circular nature of the wind direction variable. The proposed

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methodology is an improvement over previous methodologies that have proven to be successful in the simulation of uni- and multivariate time series of linear met-ocean variables (see Solari and Losada, 2011; Solari and van Gelder, 2012).

This paper is organized as follows. In Section 2 the proposed methodology and models are introduced, highlighting original features and their relevance. Section 3 presents the results obtained from applying the proposed methodology to a case study. These results are discussed on Section 4. Lastly, Section 5 summarizes the conclusions of this work. Some complementary information is included in the appendixes.

2. Methodology

As in Solari and Losada (2011, 2014) and Solari and van Gelder (2012), the proposed methodology comprises three steps. Firstly, two non-stationary probability distributions are fitted to the data. Then, these distributions are used to transform the original variables into a set of two new normalized and stationary variables. Lastly, a new model is fitted for modelling the dependency structure of the new variables (i.e. for modelling short term self-dependency or autocorrelation as well as short term dependency among the two variables or cross-correlation).

Compared to previous works, here the following innovations are introduced.

- In contrast to Solari and Losada (2014), where non-stationary distributions are fitted to the original variables (i.e. wind direction and wind speed), here non-stationary distributions are fitted to the wind direction and to the wind speed conditional to the wind direction. This allows for a better description of the joint distribution of wind speed and direction.
- Self- and cross-dependency among normalized variables (i.e. auto- and cross-correlation) are modelled by means of a vectorial autoregressive model (VAR), where the innovation process (or noise) depends on the previous values of the normalized variables and is modelled by means of a mixture distribution of wrapped multivariate normals. This approach provides great flexibility when it comes to reproducing the observed innovation process.

Next, Section 2.1 describes the proposed non-stationary probability distributions, Section 2.2 describes how other probability distributions of interest are calculated based on the fitted distributions, and Section 2.3 introduces the VAR model and describes the model proposed for the innovation process.

2.1. Non-stationary mixture distributions

2.1.1. Wind direction

For modelling the probability distribution of the wind direction ($\theta(t)$) a mixture distribution composed of N_α circular non-stationary distributions is used. The model is given by (1), where $0 \le \alpha_i(t) \le 1$, $\sum \alpha_i(t) = 1\ \forall t$, and $f_{WN,i}(\theta|t)$ are N_α non-stationary Wrapped Normal distributions (see e.g. Fisher, 1993).

$$f_\theta(\theta|t) = \sum_{i=1}^{N_\alpha} \alpha_i(t) f_{WN,i}(\theta|t) \tag{1}$$

Each of the Wrapped Normal distributions is given by the following equation:

$$f_{WN}(\theta|t) = \frac{1}{2\pi}\left(1 + 2\sum_{k=1}^{\infty} \rho(t)^k \cos\left[k\{\theta(t) - \mu(t)\}\right]\right) \tag{2}$$

where the parameters of the distribution $\rho(t)$ and $\mu(t)$, as well as the proportion parameter $\alpha(t)$ introduced in (1), are modelled by means of a Fourier series of order N_F, as given next:

$$a(t) = a_0 + \sum_{j=1}^{N_F} \left(a_j \cos(2\pi t) + b_j \sin(2\pi t)\right) \tag{3}$$

2.1.2. Wind speed conditional to wind direction

For modelling the non-stationary probability distribution of the wind speed conditional to the wind direction $(V(t)|\theta(t))$ a biparametric Weibull distribution is used

$$f_V(V|\theta,t) = \frac{B}{A}\left(\frac{V(t)}{A}\right)^{B-1} \exp\left\{-\left(\frac{V(t)}{A}\right)^B\right\} \tag{4}$$

where the parameters A and B are made non-stationary by using a Fourier approximation of order N_W, given by

$$A(t,\theta) = A_0(\theta) + \sum_{i=1}^{N_W} \left(A_{a,i}(\theta) \cos(2\pi t) + A_{b,i}(\theta) \sin(2\pi t)\right) \tag{5a}$$

$$B(t,\theta) = B_0(\theta) + \sum_{i=1}^{N_W} \left(B_{a,i}(\theta) \cos(2\pi t) + B_{b,i}(\theta) \sin(2\pi t)\right) \tag{5b}$$

with coefficients A_x and B_x $(x = 0, (a,i), (b,i)$ with $i = 1, \ldots, N_W)$ made dependent on the direction θ, also by means of a Fourier approximation of order N_W

$$A_x(\theta) = a_{Ax,0} + \sum_{j=1}^{N_W} \left(a_{Ax,j} \cos\theta + b_{Ax,j} \sin\theta\right) \tag{6a}$$

$$B_x(\theta) = a_{Bx,0} + \sum_{j=1}^{N_W} \left(a_{Bx,j} \cos\theta + b_{Bx,j} \sin\theta\right) \tag{6b}$$

2.2. Other distributions of interest

From the non-stationary probability distributions $f_\theta(\theta|t)$ and $f_V(V|\theta,t)$ it is straightforward to calculate the marginal distribution of the wind speed $f_V(V|t)$ (7a), the non-stationary joint distribution of wind speed and wind direction $f_{V\theta}(V,\theta|t)$ (7b), as well as the stationary distributions $f_\theta(\theta)$ (7c), $f_V(V)$ (7d) and $f_{V\theta}(V,\theta)$ (7e):

$$f_V(V|t) = \int_0^{2\pi} f_V(V|\theta,t) f_\theta(\theta|t)\, d\theta \tag{7a}$$

$$f_{V\theta}(V,\theta|t) = f_V(V|\theta,t) f_\theta(\theta|t) \tag{7b}$$

$$f_\theta(\theta) = \int_0^1 f_\theta(\theta|t)\, dt \tag{7c}$$

$$f_V(V) = \int_0^1 \int_0^{2\pi} f_V(V|\theta,t) f_\theta(\theta|t)\, d\theta\, dt \tag{7d}$$

$$f_{V\theta}(V,\theta) = \int_0^1 f_V(V|\theta,t) f_\theta(\theta|t)\, dt \tag{7e}$$

Also, it is immediate to estimate the expected wind speed for any given wind direction and time (taken on an yearly cycle) from the parameters $A(t,\theta)$ and $B(t,\theta)$ of the following equation:

$$\mathbb{E}(V|\theta,t) = A(t,\theta)\Gamma\left(1 + \frac{1}{B(t,\theta)}\right) \tag{8}$$

2.3. Vector autoregressive model

For modelling short-term self- and cross-dependency among the variables a Vector Autoregressive (VAR) model of order p is