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Probabilistic scheduling of offshore operations using copula based environmental time series – An application for cable installation management for offshore wind farms

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ABSTRACT

There are numerous uncertainties that impact offshore operations. However, environmental uncertainties concerning variables such as wave height and wind speed are crucial because these may affect installation and maintenance operations with potential delays and financial consequences. In order to include these uncertainties into the duration estimation, adequate tools should be developed to simulate an installation scenario for a large number of historical environmental data. Data regarding environmental time series are usually scarce and limited, therefore they should be modelled. Since the environmental variables are in reality dependent, we propose a probabilistic method for their construction using copulas. To demonstrate the effectiveness of this method compared to the cases where observed or independently constructed environmental time series are used, a realistic cable installation scenario for an offshore wind farm was simulated. It was found that the proposed method should be followed to acquire more reliable and accurate estimation of the installation's duration.

1. Introduction

During the past years a lot of attention has been drawn towards the development of renewable energy technologies due to the expected depletion of fossil fuels and respective consequences (EWEA, 2012; Dickel et al., 2014). Offshore wind energy is considered one of the most promising renewable energy sources and it is expected to grow even more during the upcoming years, because of better quality of wind far from shore, more space available and less noise and visual impact compared to onshore wind farms (Esteban et al., 2011). However, the high costs of offshore wind farms (OWF) make them non-competitive compared to the conventional energy sources. Especially installation costs highly contribute on the total cost of OWF, which "add up to nearly one quarter of the entire project value" (Wüstemeyer et al., 2015).

The installation of OWF as every offshore operation, is subject to a variety of uncertainties such as environmental conditions, failure of vessels and/or equipment, variation in the duration of operations, availability of the required components etc. However one of the main cause of miss-estimations of project duration and delays is the miss-estimation of environmental parameters, such as the wind speed and the significant wave height, which are difficult to predict in the planning phase. For those reasons, project schedulers may use buffers in the planning phase which can lead to overestimation of the duration of a project and subsequently the cost of the installation. Therefore it is essential to find a method which will assist schedulers in acquiring more accurate and reliable estimates of the duration of offshore installation operations by incorporating these uncertainties.

A lot of research has been conducted in the past regarding forecasting of environmental time series. Zounemat-Kermani and Kisi (2015) mention the following methods to model wind-wave characteristics: discrete spectral approach, stochastic simulation, numerical methods and data driven non-statistical models (such as artificial neural networks, fuzzy wavelet model, fuzzy logic and chaos theory). Moreover, a survey regarding the stochastic models for wind and wave state time series was conducted by Monbet et al. (2007) and categorizes these models into: non-parametric models, models based on Gaussian approximations and other parametric models. These methods however do not always explain the underlying physical properties which should be captured by the joint probability distribution. In particular, nothing or little may be said in terms of joint probabilities of environmental random variables that are described by a non-normal joint distribution. For example, as will be seen later on in this paper, high values of wave height may be more correlated with high values of wind

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speed than low values for each of the two variables.

Univariate distributions are used frequently in order to estimate the design parameters of wind speed and wave characteristics without considering their dependence (Yang and Zhang, 2013). Some studies were focussed on estimating the joint distribution of wave characteristics such as significant wave height and wave period. Particularly, Salvadori et al. (2013) used Copulas, Athanasoulis et al. (1994) used applications of Placket model and Galiatsatou and Prinos (2007) investigated different bivariate distributions, in order to find the dependence between significant wave height and wave period. Another example can be found in Memos and Tzanis (2000). The authors propose a model to represent the joint probability distribution of wave heights and wave periods, both in deep and shallow waters employing a wave-by-wave transformation. In Athanassoulis and Belibassakis (2002), the authors proposed a kernel density model to obtain an analytic representation of univariate or multivariate empirical distributions of metocean parameters (e.g. significant wave height, mean wave period and wave direction). This approach is particularly useful when the environmental data are only available as histograms and not historical time series. However, the aforementioned approaches were not used to produce synthetic time series. Furthermore, only a few studies investigate the joint distribution of the wind speed and the significant wave height. Particularly, Fouques et al. (2004) propose one method using only the correlation matrix and another method based on multivariate Hermite polynomials expansion of the multinormal distribution, in order to model the joint occurrence of those variables including the wave period. Moreover Bitner-Gregensen and Haver (1989, 1991) developed a joint environmental model which is based on conditional modelling approach (CMA) and concerns wind, waves, current and sea water level. This model was also applied for design and operations of marine structures by calculating the joint distribution based on parametric fits for each one dimensional marginal (Bitner-Gregersen, 2015). Also the Nataf model (Nataf, 1962) is used in many applications in literature for modelling metocean variables. Nevertheless, in Bitner-Gregersen et al. (2014), it is noted that Nataf model may lead to bias results, when the transformation to standard normal variates deviates from a multinormal distribution. Finally, Yang and Zhang (2013) followed a similar approach as the one described in this article, using Copulas to estimate the joint distribution of wind speed and significant wave height without taking into account the autocorrelation which is essential when time series are required.

The main goal of this article is to propose an alternative method to produce large number of realistic time series of wind speed and significant wave height, which can be valuable for planning and scheduling more efficiently offshore installation operations. In order to plan the sequence of complex offshore installation operations and decide the optimal combination of vessels and equipment required for a particular operation, different scenarios should be simulated and compared. Therefore, large number of environmental time series is needed to account for uncertainties regarding the environmental conditions that limit the operations. Usually it is difficult, expensive and sometimes impossible to acquire a large data set of environmental time series and when it is possible there are often missing values due to failures in the measuring equipment (Monbet et al., 2007), which can influence the estimation of the duration of offshore operations. For these reasons it is important to create realistic environmental time series by taking into account the dependence between the environmental characteristics. In this paper a method using copulas is proposed in order to produce time series of environmental characteristics that limit the operations (i.e. wind speed and significant wave height) by taking into account their dependence and the observed autocorrelation. Copulas are a way of studying scale free measures of dependence and a starting point for constructing families of bivariate distribution (Nelsen, 2006). Copulas allow us to construct models which go beyond the standard ones at the level of dependence (Embrechts et al., 2003) and they avoid the restriction that presents the traditionally used method which describes the pairwise dependence using families of bivariate distribution characterized by the same parametric family of univariate distributions (Genest and Favre, 2007). Following the copula approach, it is possible in many cases to construct the joint distribution requiring only the marginal distributions of the variables and measures of their dependence (Clemen and Reilly, 1999). Also, in our case, the characterization of the joint distribution of the environmental variables of interest is semi-parametric. In other words, the one dimensional margins are modelled by non-parametric estimators while the underlying dependence structure are described by one parameter copulas. Moreover the use of copulas has made the investigation of asymmetries in the joint distribution relatively easier since they satisfy different types of tail behaviour (Joe, 2014). These asymmetries are, as it shall be demonstrated in this paper, crucial for offshore operations which are mainly influenced by extreme environmental conditions. Finally, in order to investigate the effect of this approach, an application of the proposed method concerning the estimation of the duration of the cable installation of an offshore wind farm was conducted.

2. Preliminary concepts and definitions of copulas

Before continuing to the method proposed for the construction of time series for significant wave height and wind speed, the main concepts and definitions to be used in the remainder of this paper are introduced. Copulas are defined as functions that join or "couple" multivariate distribution functions to their one-dimensional marginal distribution functions. In particular, they are multivariate distribution functions whose one-dimensional margins are uniform on the interval $[0,1]$ (Nelsen, 2006). The most important theorem of copulas theory is Sklar's theorem (Sklar, 1959) which states that any multivariate joint distribution can be written in terms of the univariate marginal distribution functions and a copula which describes the dependence between the random variables. For the two dimensional case let $H_{XY}(x, y)$ be a joint distribution function with marginal distribution $F_X(x)$ and $G_Y(y)$ which lie in the interval [0,1]. Then there is a copula C on the unit square I^2 such that for all x, y satisfies the following (Genest and Favre, 2007):

$$H_{XY}(x, y) = C\{F_X(x), G_Y(y)\}x, y \in \mathbb{R} \tag{1}$$

There is a large variety of copulas which can be used to model joint distributions with different characteristics. For the purpose of this paper three of the most common families of copulas are investigated: the Gaussian, Gumbel and Clayton copulas. These copulas can model different tail asymmetries of the joint distributions and have been used in many financial applications (e.g. see Aas et al., 2009).

The Gaussian copula is given by:

$$C(u, v) = \Phi_\rho\left(\Phi^{-1}(u), \Phi^{-1}(v)\right) \tag{2}$$

where Φ denotes the standard normal distribution function and Φ_ρ the standard bivariate normal distribution function with linear correlation coefficient ρ.

The Gumbel and Clayton copulas are two of the most used one-parameter Archimedean copulas. For the bivariate case, Archimedean copulas are defined as $C(u, v) = \varphi^{-1}\left(\varphi(u)+\varphi(v)\right)$. The