

Modelling and Evaluation of Wind Speed Time Series for Reliability Analysis of Offshore Wind Farms

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ABSTRACT

This paper outlines proposed testing criteria for wind speed time series (WSTS) models. The objective is to assess their suitability for reliability analysis that is dependent on an accurate representation of weather patterns. Two WSTS models were analysed for their suitability against these criteria. The Markov model was found to be suitable for resource assessment, but would require modification before it could represent weather patterns, whilst the random sampling model could represent weather patterns more accurately, but could not be used for resource assessment.

I. INTRODUCTION

In order to meet EU renewable energy penetration targets for 2020 and beyond, the Levelised Cost of Energy (LCoE) of offshore wind needs to be reduced from the current £140/MWh to be lower than £100/MWh [1]. To facilitate this, innovation in planning and operation is required, including the cost-benefit analysis of improving farm availability. As operation and maintenance accounts for around 30% of the LCoE [2], a number of researchers have carried out reliability studies on offshore wind.

One of the unique characteristics of wind generation is the stochastic nature of the fuel. As such, a number of these reliability studies aim to capture the stochastic nature of the wind resource, with a particular focus on a site's mean wind speed. As local wind speed data for a particular site is limited by the length of time a meteorological mast has been installed at the site, long term reliability studies require the wind speed to be simulated based on this limited data. This modelling has been carried out in a number of ways:

- Mathematical expectation calculations based on probability distribution functions [3].
- Wind speed time series (WSTS) produced by randomly sampling from probability distributions [4].
- WSTS produced from Markov processes [5].
- WSTS produced using an auto-regressive moving average (ARMA) model [6].

Mathematical expectation calculations can be used to quickly assess the performance of a wind farm configuration, but cannot be used to detail the effects of factors such as weather windows and maintenance delays. The production of WSTS is more appropriate for investigating these factors. For example, the use of a WSTS can more accurately represent the effect of a turbine failure by giving the range of impacts that may occur, along with their respective likelihood. This can give a confidence level in the energy production produced by the model. Therefore, the production of WSTS models is the focus of this research.

Whilst each method has qualitative benefits and disadvantages that may determine which method is used for reliability analysis, no work has been done to quantify whether the models produce similar values for key parameters such as the wind's available energy. This analysis is needed to justify the use of these WSTS models.

The paper is organized as follows. Section II details the tests to be carried out on WSTS models to assess their suitability. Section III gives information on two example WSTS models that has been tested. Section IV details the results of the tests carried out on the WSTS models. Section V summarises the conclusions from this work.

II. METHODOLOGY

To assess the quality of a WSTS model, an original data set is required. The original WSTS was taken from the meteorological mast at the Egmond aan Zee wind farm site [7]. Wind speeds from a height of 70 m, at 10 minute intervals from 01/07/2005 to 30/06/2006 were used, and the data has been cleaned to produce a complete data set.

To quantify the suitability of a WSTS generator for reliability analysis, the key measures needed to be considered:

- Produce an amount of energy in the wind close to that of the original WSTS.
- Produce an amount of energy from a typical wind turbine close to that of the original WSTS.
- The total time at all wind speeds should be similar to the original WSTS.
- Produce a similar number of transitions between wind speeds to the original WSTS.
- Capture the longer term seasonal trends and occurrence of sustained low and high wind speeds in the data.

By quantifying these measures, a metric was produced which could assess the adequacy of any WSTS model; the closer the measured metrics are to the original WSTS, the better the model. The following paragraphs detail how these metrics were quantified. Note, the wind speeds were discretized into 1 m/s bins, except for the frequency analysis.

To quantify energy availability, the expected power densities of original and produced WSTS were computed (1). Expected power density was used to remove any unrequired information such as turbine size and turbine life span.

$$E(p) = \sum_{u=0}^{u_{max}} 0.5\rho u^3 F(u) \quad (1)$$

Where $E(p)$ is the expected power density (W/m^2), ρ is air density (kg/m^3), u is wind speed (m/s), u_{max} is the maximum wind speed (m/s) and $F(u)$ is the probability distribution function of the wind speeds.

The expected power from a typical turbine was computed in the same way (2), but with limits to represent the cut-in, cut-out and rated wind speeds (3). The parameters of the wind and wind turbine can be found in Table 1.

$$E(p_t) = \sum_{u=0}^{u_{max}} 0.5C_p\rho u_t^3 F(u) \quad (2) \quad u_t = \begin{cases} 0, & u < u_{in} \\ u, & u_{in} \leq u < u_{rated} \\ u_{rated}, & u_{rated} \leq u < u_{out} \\ 0, & u \geq u_{out} \end{cases} \quad (3)$$

Where $E(p_t)$ is the expected power density from a typical turbine (W/m^2), C_p is the coefficient of performance, u_t is the equivalent wind speed for a wind turbine (m/s), u_{in} is the cut-in wind speed (m/s), u_{rated} is the rated wind speed (m/s), and u_{out} is the cut-out wind speed (m/s).

Parameter	Value	Parameter	Value
u_{in}	4 m/s	ρ	1.225 kg/m^3
u_{rated}	13 m/s	C_p	0.4
u_{out}	25 m/s		

Table 1: Parameter values for expected power calculations.

To compare the total time at all wind speeds, the total time at each wind speed for each WSTS were represented on a bar chart. The number of transitions between wind speeds was also counted and compared to the original WSTS.

To assess the quality of seasonal representation, two tests were carried out. Firstly, the frequency spectrum of the produced WSTS was compared to the original WSTS by taking their Fourier Transform (FT). In the spectrum, the frequencies for both WSTS should have similar amplitudes if the seasonal variation has been modelled successfully.

The second test quantified the occurrence of weather windows. A weather window is defined as a point in time where a maintenance team could be dispatched to repair a component offshore as the wind speed is below a threshold for a time period long enough to carry out the repair. This was quantified by calculated the percentage of time a maintenance team could be dispatched. The length of the weather window and the wind speed threshold is dependent on the type of maintenance being carried out and the travel distance. For this work, targets of a wind speed threshold of 10 m/s and a time of 48 hours was taken as a weather window, similar to those found for a jack-up vessel in [8].

To summarise, for the produced WSTS the $E(p)$, $E(p_t)$, wind speed residence times, the number of wind speed transitions, the frequency spectrum, and the percentage of time a weather window is available were compared to the original WSTS to assess the quality the WSTS models used.

III. WSTS MODEL EXAMPLES

Two WSTS models were analysed; a continuous-time Markov process model developed for this work, and a model that randomly samples from various probability distributions [4]. These two methods are outlined in this section.

The Markov process uses only the transitions between wind speeds within a real WSTS to dictate the transitions occurring in the produced WSTS. Like the random sampling from a probability function, the use of probabilities retains the stochastic nature of the wind but can capture how the WSTS moves between wind speeds more accurately. However, the calculation of transition rates introduces more complexity and requires a larger amount of data.

A Markov process approach assumes that the system is memory-less; future random behaviour is only dependent on the current state, and the process is stationary; the behaviour of the system is time independent. As such, the transition rates must be constant. The state residence times are assumed to follow an exponential distribution [6]. The transition rates are calculated using (4). The transitions times from the current state i to state j are calculated using (5).

$$\lambda_{ij} = \frac{N_{ij}}{T_i} \quad (4) \quad L_{ij} = \frac{h_{yr}}{\lambda_{ij}} \ln(R_j) \quad (5)$$

Where λ_{ij} is the transitions rate between states i and j (occurrences/year), N_{ij} is the number of transitions between states i and j , T_i is the total time at state i (years), L_{ij} is the transition time between state i and j (hours), h_{yr} are the number of hours in a year (8760), and R_j is a uniform random number between 0 and 1.

The Markov process model used is similar to that found in [5], with a number of key features:

- The initial state is determined by randomly sampling from a Weibull distribution based on the original WSTS.
- The input data is based on 10 minute average, rather than hourly average, wind speed data.
- Missing transition rates in the transition matrix due to having a small dataset were filled using linear interpolation.
- Transitions can occur to any other state from the current state, unlike the birth-and-death model used in [5]. The next state is determined by the smallest transition time calculated (5) and states are represented by 1 m/s bins.
- The original data was sampled at 10 minutes, so transitions that occur within 10 minutes of the current state in the model are rejected. As a continuous process is used, transition times can be a non-integer multiple of 10 minutes to produce a continuous-time WSTS.

For comparison, a WSTS model that randomly samples from Weibull and normal distributions with a smoothing algorithm was also tested against these criteria. The details of this WSTS model can be found in [4], but the model has been modified to produce 10-minute average wind speeds, rather than hourly average wind speeds.

Two WSTS models have been detailed here. A Markov process was used, with 1 m/s wind speed bins as states, and the process could move from the current state to any other state. The model used transition rates that were modified to minimise the effect of small data sets. Any transitions below 10 minutes were rejected. Another WSTS model based on randomly sampling from probability distributions was also used for comparison.

IV. RESULTS AND DISCUSSION

A WSTS lasting 8760 hours was produced 1000 times from both wind speed models so that a representative mean could be produced for each parameter, except for the frequency spectrum production. Figure 1 compares the residence times between original and produced WSTS, Figure 2 compared the results of the FT applied to the original and a sample produced WSTS, and Table 2 summarises the results of the time series testing.

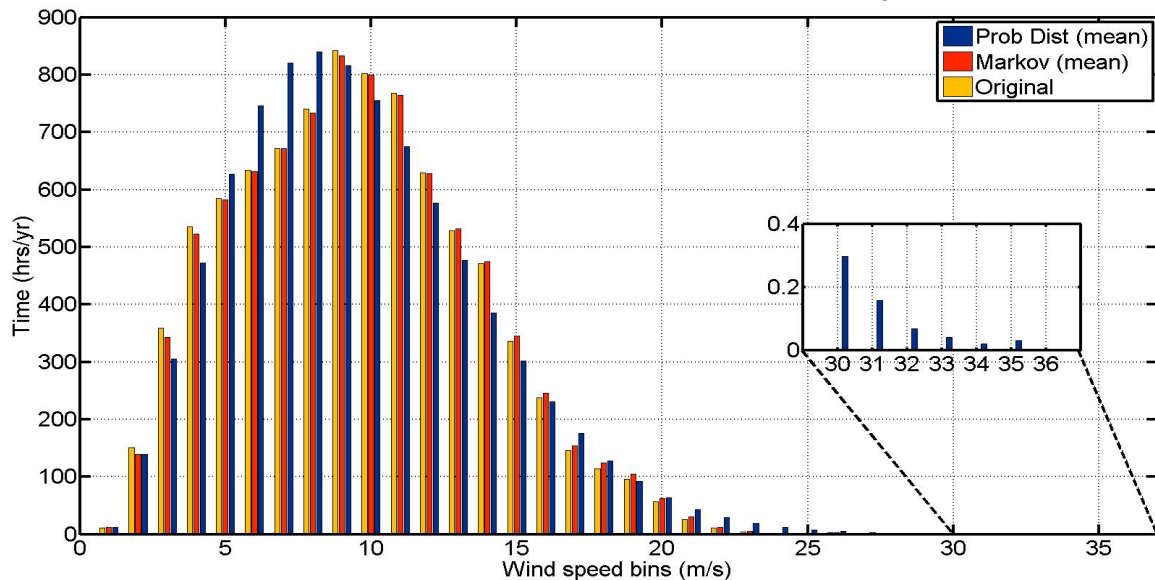


Figure 1: Comparison of wind speed bin residence times for original and mean of produced WSTS.

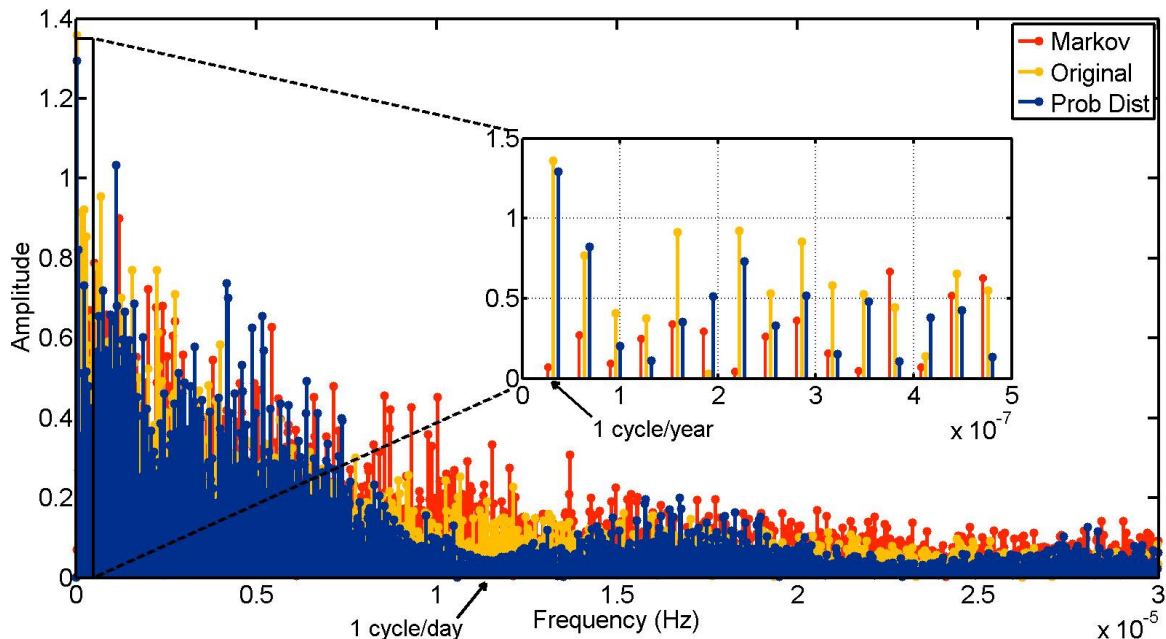


Figure 2: Frequency spectrum of original and produced WSTS.

Test criteria	Original time series	Markov Process (mean)	Probability Distribution (mean)
$E(p)$ (W/m ²)	657.3	678.8	692.7
$E(p_t)$ (W/m ²)	510.9	519.8	493.7
Number of wind speed transitions	19378	16244	41970
Weather window opportunities (%)	14.8	4.6	24.1

Table 2: Results of analysis of original WSTS and produced WSTS.

Firstly, $E(p)$ and $E(p_t)$ from the Markov process were 3.19% and 1.10% higher respectively than that of the original WSTS (Table 2). This is reflected in Figure 1, where the wind speeds are biased towards higher wind speeds. However, as this over-estimation is small, the Markov process is appropriate for capturing energy characteristics. In contrast, $E(p)$ for the random sampling method was 5.4% higher than the original WSTS, but $E(p_t)$ was 3.4% lower. The high $E(p)$ can be attributed to the higher wind speeds (Figure 1), whilst the lower $E(p_t)$ was due to the higher total time at lower wind speeds. Therefore the Markov process produces a more accurate energy availability estimate.

Secondly, Figure 1 reveals that the produced WSTS from the Markov process reproduced the total residence time at different wind speeds with some accuracy, though tended to favour higher wind speeds. The number of wind speed transitions was lower than in the original WSTS (Table 2) indicating that the Markov process had residence times that were longer than of those in the original WSTS. This suggests that an exponential distribution is not the best distribution to represent residence times. However, the random sampling method was a poor estimation of wind speed bin times (Figure 1) and produced more transitions (Table 1). Therefore, the Markov process represents the wind speed times and transitions numbers more accurately than the random sampling method.

Finally, Figure 2 reveals that the seasonality of the original WSTS (represented by peaks at the low frequencies) was not captured by the Markov Process. This reveals that seasonality should be added to any WSTS model using a Markov Process. The random sampling method used mean speeds for each month, and therefore replicated the high amplitude peaks at low frequencies of the original WSTS with some accuracy (Figure 2). Furthermore, the reduced number of weather windows (Table 2) indicates that the Markov process moved between low and high wind speed states more regularly than the original data. This is highlighted by the higher magnitudes around 10^5 Hz (~1 cycle/day) (Figure 2). The random sampling method was slightly more accurate at depicting weather windows, but did overestimate their occurrence (Table 2) due to the reduced number of high frequency transitions (Figure 2).

A basic continuous Markov process can be used for macro-scale resource assessment for a site as it represents the power densities and total residence times whilst maintaining the random nature of the wind, but this random sampling approach is inadequate. However, the Markov process is not a valid approach when analysing for effects of weather windows on maintenance, or reliability analysis that requires seasonality, without the need for detailed modifications to the process, whilst the random sampling approach captures seasonality more accurately.

V. CONCLUDING REMARKS

The features required of a produced WSTS for reliability analysis and the tests designed to assess the suitability of proposed WSTS models based on these features are detailed here. Example WSTS models in the form of a continuous Markov process and random sampling from probability distributions were analysed against these criteria. It was found that a basic Markov process would be suitable for resource assessment reliability analysis which required a stochastic wind resource. However, the basic model would require modification in order to capture more complex weather patterns before it would be suitable for more detailed reliability analysis. Conversely, this random sampling method is more accurate at producing seasonal variations, but cannot be used for resource assessment.

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