Modelling wind speeds using CorRES: Combination of mesoscale reanalysis data and stochastic simulations

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***Abstract*—The simulation tool CorRES models wind speed in two parts. A deterministic part which uses meteorological reanalysis data and a stochastic part modelling the short-term variability not captured in the reanalysis data. The two parts of this model have been validated separately. The validation and parameterisation of their combination is the topic of this paper. The models are tested and parameterised using measured data from three different locations. The effect of the height and year of measurement, on the parameters of the model is also studied. The results of this paper indicate that the best-fitting parameters depend on the measurement location and height.**

I. Introduction

A. Motivation

The power generated by a wind turbine depends on the weather conditions, which makes it a highly volatile power source. For example, its short-term volatility affects the reactive power support the wind turbine can provide and thereby the voltage stability [1], [2]. Thus, to ensure the reliable operation of grids including wind turbines it is essential to model in detail the source of volatility, i.e. the wind speed.

B. Literature Review

Correlations in Renewable Energy Sources (CorRES) is a simulation tool developed at the Technical University of Denmark, Department of Wind Energy [3]. CorRES can be used to simulate the wind speed and/or the wind power output at a specific location or for a specific system. It uses the Weather Research and Forecasting (WRF) mesoscale model to produce hourly wind speed time series on a 10 km x 10 km grid covering the area of interest [4], [5]. A limitation of this mesoscale model and other similar models is that they tend to underestimate the short-term wind variability [6].

To improve the modelling of the short-term fluctuations in wind speed compared to using WRF data on its own, CorRES includes a stochastic modelling component. The stochastic fluctuation model is defined through its Power Spectral Density (PSD) function [7]. In this work, the low frequency spectrum used in [7] is replaced by the one presented in [6]; the spectra slope -5/3 presented in [6] provides a strong theoretical and empirical foundation for correcting the WRF data PSD for the higher frequencies, where spectral correction is required. These two parts of the wind speed model, i.e. the mesoscale reanalysis data and the stochastic model, have been validated independently [7], [8]. However, their combination has not yet been validated. The parameter selection for the fluctuation spectra is dependent on the WRF data spectra. Thus, the PSD of the WRF data and the additional PSD of the fluctuations need to be considered jointly to understand the resulting PSD of the simulated wind speed data.

C. Contributions

In this paper, the CorRES model is tested using 10 minutely averaged data from three different locations [9], [10]. It is considered how the parameterisation of the stochastic model may differ for the different locations, different heights and even different years. Through statistical analysis of the data, the paper provides an approach to determine the parameters for these three locations and analyse how they compare for different heights. This approach can be used to find the best-fitting parameters for any location/data set.

D. Paper Organisation

The remainder of this paper is organised as follows. Section II describes the wind speed modelling in the CorRES simulation tool. In Section III, the three data sets used to test the CorRES wind speed modelling method are presented. The fitting of the data sets and the resulting parameterisation of the CorRES models are discussed in Section IV. Finally, in Section V conclusions are drawn.

II. Wind speed modelling in CorRES

This section presents the modelling of wind speed in the CorRES simulation tool. The models in CorRES consist of two parts; the meteorological reanalysis data (see Section II-A) and stochastic models (see Section II-B). CorRES is able to simulate wind speed time series that capture the temporal and spatial variations in wind speed by combining the two as presented in Section II-C.

A. Meteorological reanalysis data

CorRES wind speed models are based on meteorological reanalysis data obtained from the Weather Research and Forecasting (WRF) model [4]. WRF is a mesoscale modelling system. Thus, the down-scaling method presented in [5] is used. The WRF model produces hourly wind speed time series on a 10 km x 10 km grid covering the considered area. Wind speed variations in the WRF data are smoothed due to spatial and temporal averaging effects. Additionally, as the WRF data is hourly, it does not model inter-hour variations. Therefore, short-term wind speed fluctuations are captured through the stochastic model added to the WRF data as shown in Section II-B.

B. Stochastic simulation

The stochastic fluctuation model models the short-term variability that is generally lacking in WRF data [6]. The framework of stochastic fluctuation modelling, and how to apply it in time series simulation, is presented in [7]. The fluctuations modelling includes the modelling of the wind speed PSD for individual locations and the coherence between locations.

The temporal behavior of fluctuations at each wind power plant is modelled by specifing its PSD. The wind speed PSD at frequencies that are lacking variability in WRF data can be expected to follow a $-5/3$ power law as has been shown in [6]. The PSD of the stochastic fluctuation models, providing the additional variability missing in mesoscale reanalysis data, is modelled as:

$$S_{lf}(f) = \frac{a_1}{f_0^{5/3} + f^{5/3}} \text{ for } f > f_0, \tag{1}$$

where f is frequency and a_1 is the coefficient of the spectra. Fluctuations are added only on frequencies higher than f_0. In addition to (1), the stochastic fluctuation simulation model in CorRES considers turbulence, as shown in [7]. However, the addition of the turbulence PSD has a very small influence on the studied 10 minute resolution and is therefore not considered in this work.

C. Combining reanalysis data and fluctuations

The CorRES wind speed model is a combination of the WRF reanalysis data, v_t^{WRF}, and the simulated fluctuations, v_t^{flucts}. Thus,

$$v_t = v_t^{\mathrm{WRF}} + v_t^{\mathrm{flucts}} \tag{2}$$

where v_t is the wind speed time series generated in CorRES. In CorRES the wind speeds for multiple locations can be simulated simultaneously. The v_t^{WRF} is correlated spatially and temporally and so is the v_t^{flucts} component. v_t^{flucts} has the expected value zero. Therefore, it does not affect the long-term mean wind speed of the v_t^{WRF}.

In Figure 1 an example of the Power Spectral Density (PSD) of the WRF data with and without fluctuations is shown. In this case the parameters for the PSD in (1) are $a_1 = 2.5 \cdot 10^{-4}$ and $1/f_0 = 8$ hours. It shows that by adding the fluctuations, v_t^{flucts}, to the WRF data, v_t^{WRF}, the PSD for the higher frequencies is increased.

Example wind speed time series generated in CorRES are shown in Figure 2. When v_t^{WRF} is considered on its own the inter-hour wind speed is determined through linear interpolation.

The wind speed fluctuations, modelled using (1), are dependent on the two parameters, namely f_0 and a_1. The parameters define the intensity (a_1) and the frequency range (f_0) of the generated fluctuations. Two v_t time series were different f_0 and a_1 parameters are utilized are compared in Figure 2. The difference between the two time series highlights how much the modelled wind speed fluctuations may vary dependent on the selected parameters. Through the tuning of the parameters, a_1 and f_0, the PSD of v_t can be set to match the PSD of measured wind speed data and thereby produce more realistic wind speed time series.

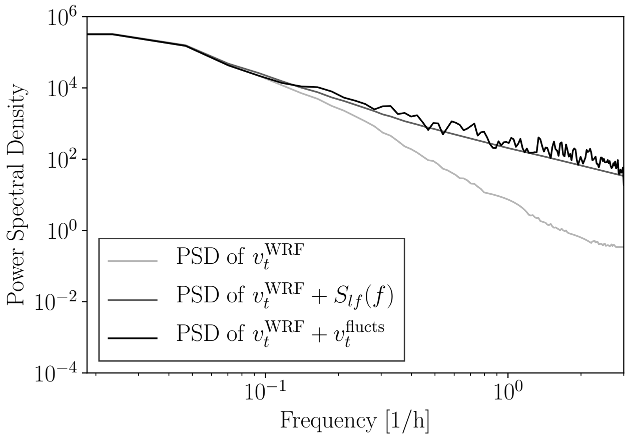

Figure 1. Example PSD of v_t^{WRF} with the theoretical fluctuations as defined in (1), with stochastic simulated fluctuations v_t^{flucts} and without including fluctuations.

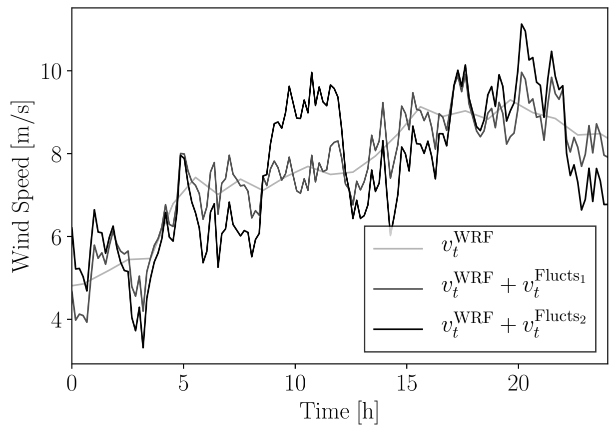

Figure 2. Example time series of WRF data with and without fluctuations. The different fluctuation scenarios are: $\mathrm{Flucts_1}$ where $a_1 = 2 \cdot 10^{-4}$ and $f_0 = 1/5$ h and $\mathrm{Flucts_2}$ where $a_1 = 3 \cdot 10^{-4}$ and $f_0 = 1/13$ h.

III. Wind speed data sets

To validate and parameterise the wind speed model presented in Section II three sets of wind speed data are considered. The details of these data sets are presented in Table I. Each data set consists of wind speed measurements sampled every 10 minutes in an onshore location.

Table I
THE THREE SETS OF MEASURED WIND SPEED DATA.

Data Set	Name	Location	Hub heights [m]	Time
1	Hovsore	56.44°N, 8.15°E	80	5 years (2006-2010)
2	Cabauw	51.97°N, 4.93°E	80	6 years (2001-2006)
3	Risø	55.69°N, 12.09°E	77	4 years (2000-2003)

Data Set 1 and 3 include measurements collected for the DTU Online Meteorological Data base [9]. This data base includes wind speed measurements from several locations in Northern Europe including Greenland, Denmark, Sweden and Faroe Islands. The two data sets (Hovsore and Risø) studied in this paper include measurement data collected in Denmark.

Data Set 2 includes measurements gathered at the Cesar Observatory located in the western part of the Netherlands. These measurements are publicly available in [10].

IV. Results

In this section the CorRES wind speed models presented in Section II are utilized to model the three data sets presented in Section III. To determine the best parameters for the CorRES stochastic fluctuation model the autocorrelation of the data and the simulated time series are compared as discussed in Section IV-A. The simulated time series and the best-fitting parameters for each scenario are presented in Section IV-B and the results discussed in Section IV-C.

A. Fitting

Autocovariance is the equivalent of the Power Spectral Density (PSD) in the time domain. The standard deviation of the wind speed time series simulated using CorRES is mostly defined by the reanalysis data as the fluctuations only impact the higher frequencies. The autocorrelation is the normalized autocovariance. That is the autocovariance with the effect of the standard deviation removed. For these reasons, the autocorrelation is chosen as a comparison metric for the selection of the best fluctuation model parameters.

Figure 3 shows the autocorrelation of CorRES wind speed time series with and without fluctuations for Data Set 1. Results show that the WRF data on its own does not capture the autocorrelation of the data for the first few hours. By adding the stochastic fluctuations to the WRF data the autocorrelation can be shifted to better match the autocorrelation of the measured data.

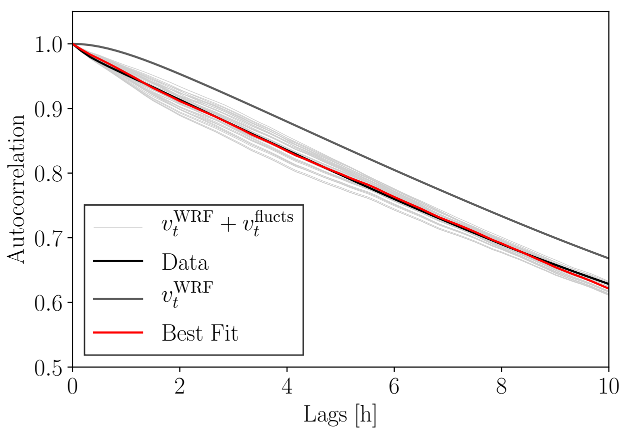

Figure 3. The autocorrelation of Data Set 1 (in black), of the time series simulated using CorRES without fluctuations (dark grey) and with fluctuations (lighter grey) for the different parameter combinations as listed in Table II. The autocorrelation of the best-fitting simulated time series ($1/f_0 = 10$ hours and $a_1 = 2 \cdot 10^{-4}$) is shown in red.

To analyse the fit of the simulated time series, compared to measured data, the Root Mean Square Error (RMSE) of the autocorrelations is found as:

$$\mathrm{RMSE_{ACF}} = \sqrt{\frac{\sum_{i=0}^{h}(y_i - x_i)^2}{h}}, \tag{3}$$

where y_i and x_i are the autocorrelation of the modelled time series and the measured data at time lag i, respectively. The parameter h defines how many hours of time lags are considered for the comparison. In this work h is selected to be 10 hours.

The simulated time series utilizing different fluctuation parameters are compared through their computed $\mathrm{RMSE_{ACF}}$ values. The lower the $\mathrm{RMSE_{ACF}}$ value the better the fit.

B. Simulation

The wind speed fluctuations, modelled using (1), are dependent on the selection of the two parameters, namely f_0 and a_1. The parameters define the intensity (a_1) and the frequency range (f_0) of the generated fluctuations.

In [6] it is shown that the reanalysis data may lack variability in time scales of upto a few hours. This is demonstrated in Figure 4 for the measured data of Data Set 1 and the equivalent WRF data. The PSD of the WRF data becomes less accurate for frequencies of about $1/10$ hours^{-1}. This inaccuracy can be corrected in part by adding stochastic fluctuations. The f_0 parameter for the stochastic fluctuations model is set according to this. Therefore, in this paper the f_0 parameter is tested in the range $1/f_0 = 4 - 13$ hours. This range for f_0 is highlighted in Figure 4.

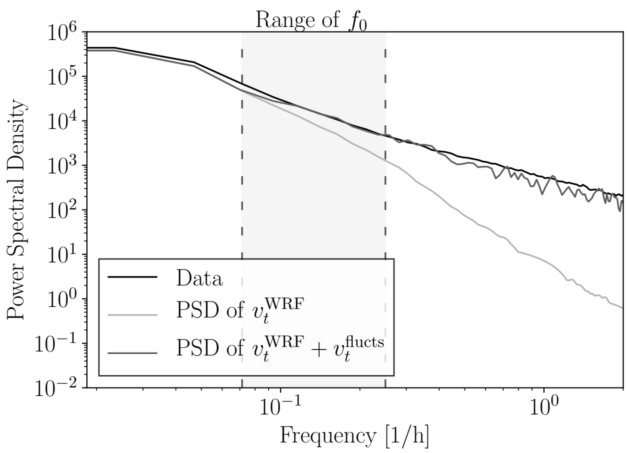

Figure 4. The PSD of the measured data of Data Set 1 and the equivalent WRF data with and without fluctuations. In this case the fluctuation parameters are set to be $a_1 = 2.5 \cdot 10^{-4}$ and $1/f_0 = 10$ hours.

In [11], the parameter a_1 is identified to be $3 \cdot 10^{-4}$ for an offshore location in Denmark. However, in that case study, the parameter a_1 was selected for modelling the PSD without considering the contribution of the PSD of the WRF data in the higher frequencies. Thus, in this paper $a_1 = 3 \cdot 10^{-4}$ is the highest value considered and lower values $a_1 = [1.5, 2, 2.5] \cdot 10^{-4}$ are also considered.

To find the best parameter combination, for a_1 and f_0, 40 combinations are tested. These combinations are listed

Table II
THE $\mathrm{RMSE}_{\mathrm{ACF}}$ VALUES FOR THE DIFFERENT PARAMETER COMBINATIONS FOR MODELLING DATA SET 1 MEASURED AT HEIGHT 80 METERS. THE LOWEST $\mathrm{RMSE}_{\mathrm{ACF}}$ AND THEREBY THE BEST FIT IS HIGHLIGHTED IN RED.

$1/f_0$ [hour]\ a_1	$1.5 \cdot 10^{-4}$	$2 \cdot 10^{-4}$	$2.5 \cdot 10^{-4}$	$3 \cdot 10^{-4}$
4	0.0179	0.0152	0.0127	0.0103
5	0.0163	0.0131	0.0101	0.0075
6	0.0138	0.0106	0.0073	0.0053
7	0.0125	0.0086	0.0057	0.0057
8	0.0109	0.0067	0.0047	0.0069
9	0.0086	0.0046	0.0046	0.0089
10	0.0053	0.0026	0.0066	0.0123
11	0.0045	0.0027	0.0076	0.0136
12	0.0032	0.0042	0.0107	0.0173
13	0.0031	0.0052	0.0119	0.0187

in Table II. The autocorrelation of the measured data is compared to each of the autocorrelation functions of the time series generated using CorRES with the different parameter combinations. Table II shows the $\mathrm{RMSE}_{\mathrm{ACF}}$ values for the fit of Data Set 1 at height 80 meters for the full data set, that is years 2006-2010. In this case the best parameters are gound to be $a_1 = 2 \cdot 10^{-4}$ and $1/f_0 = 10$ hours as highlighted in Table II. In Figure 3 the autocorrelation for Data Set 1, at height 80 meters and the 40 simulated CorRES time series is shown. The best fit is highlighted in red. This analysis is repeated for each case in the remainder of this study to find the best parameter combination.

Furthermore, the effect of the measurement height and measurement year on the parametrisation of the stochastic model is studied for Hovsore (Data Set 1). Each year of data in Data Set 1, that is 2006 through 2010 is considered individually for two different measurement heights, 80 and 100 meters. The best-fitting parameters for each case are presented in Table III (a). From Table III (a) it can be observed that typically for higher measuring heights the a_1 parameter is bigger while the $1/f_0$ parameter is smaller. The best parameters also vary between years with a_1 ranging from $1.5 - 2.5 \cdot 10^{-4}$ and the $1/f_0$ value ranging from $7 - 11$ hours.

The same analysis is done for the two remaining data sets, Data Set 2 and 3. For Data Set 2 the years 2001 through 2006 are analysed for measurement heights 80 and 140 meters. The results for Data Set 2 are presented in Table III (b). In the case of Data Set 3 the years 2000 to 2003 are analysed at measurement heights 77 and 125 meters and the results are outlined in Table III (c). Both data sets demonstrate the same results as Data Set 1, that is the best-fitting parameters change with height and year. Further discussion on the results is provided in the following section, Section IV-C.

C. Discussion

The results in Table III indicate that the parameter a_1 may range from $1.5 - 3 \cdot 10^{-4}$ while $1/f_0$ ranges between

Table III
THE BEST-FITTING PARAMETER COMBINATIONS FOR THE THREE DIFFERENT DATA SETS. EACH TABLE CONTAINS THE BEST PARAMETERS FOUND FOR EACH YEAR OF MEASURED DATA FOR TWO DIFFERENT MEASUREMENT HEIGHTS. THE PARAMETERS LISTED IN THE TABLE ARE THE MEAN VALUE (μ) AND THE STANDARD DEVIATION (σ) OF THE MEASURED DATA AS WELL AS THE BEST-FITTING PARAMETERS a_1 AND f_0 FOR THE FLUCTUATION MODEL IN (1).

(A) DATA SET 1 (HOVSORE).

Year\Height	80 m				100 m			
	μ	σ	a_1	$1/f_0$	μ	σ	a_1	$1/f_0$
2006	8.5260	4.0389	$1.5 \cdot 10^{-4}$	11	8.8057	4.1848	$2 \cdot 10^{-4}$	9
2007	9.4431	4.7028	$2 \cdot 10^{-4}$	11	9.7571	4.8270	$2 \cdot 10^{-4}$	9
2008	9.0925	4.5756	$2.5 \cdot 10^{-4}$	11	9.4034	4.7137	$2.5 \cdot 10^{-4}$	10
2009	8.5796	4.0661	$2 \cdot 10^{-4}$	9	8.8984	4.1823	$2.5 \cdot 10^{-4}$	7
2010	8.3104	3.8343	$1.5 \cdot 10^{-4}$	10	8.7134	3.9643	$2.5 \cdot 10^{-4}$	8
2006-2009	8.7905	4.2771	$2 \cdot 10^{-4}$	10	9.1158	4.406	$2.5 \cdot 10^{-4}$	8

(B) DATA SET 2 (CABAUW).

Year\Height	80 m				140 m			
	μ	σ	a_1	$1/f_0$	μ	σ	a_1	$1/f_0$
2001	6.7988	2.9904	$2.5 \cdot 10^{-4}$	9	7.8288	3.5034	$3 \cdot 10^{-4}$	9
2002	7.0747	3.4289	$1.5 \cdot 10^{-4}$	9	8.1122	3.9629	$2 \cdot 10^{-4}$	9
2003	6.5109	2.9303	$2 \cdot 10^{-4}$	11	7.5091	3.4980	$2.5 \cdot 10^{-4}$	9
2004	6.9012	3.3291	$2 \cdot 10^{-4}$	10	7.9137	3.8754	$3 \cdot 10^{-4}$	8
2005	6.6889	3.1153	$1.5 \cdot 10^{-4}$	9	7.7016	3.6787	$2 \cdot 10^{-4}$	9
2006	6.9716	3.0583	$2.5 \cdot 10^{-4}$	9	8.0228	3.5998	$3 \cdot 10^{-4}$	9
2001-2006	6.8243	3.1527	$2 \cdot 10^{-4}$	9	7.8481	3.6961	$2.5 \cdot 10^{-4}$	9

(C) DATA SET 3 (RISØ).

Year\Height	77 m				125 m			
	μ	σ	a_1	$1/f_0$	μ	σ	a_1	$1/f_0$
2000	7.0311	3.2968	$2 \cdot 10^{-4}$	10	8.7038	3.1286	$3 \cdot 10^{-4}$	8
2001	6.7525	3.1746	$1.5 \cdot 10^{-4}$	10	7.5280	3.4895	$2.5 \cdot 10^{-4}$	8
2002	6.9965	3.2493	$2 \cdot 10^{-4}$	11	7.3052	4.4228	$2.5 \cdot 10^{-4}$	9
2003	6.6988	3.3463	$2 \cdot 10^{-4}$	11	6.8625	4.0146	$2.5 \cdot 10^{-4}$	9
2000-2003	6.7610	3.3463	$2 \cdot 10^{-4}$	10	7.3789	3.8901	$2.5 \cdot 10^{-4}$	9

7 and 11 hours depending on the measurement year, height and location. It can be observed that the best-fitting values for a_1 and $1/f_0$ are dependent on one another. This is further demonstrated with the scatter plot of a_1 and $1/f_0$ values in Figure 5. For larger values of a_1, the corresponding value of $1/f_0$ tends to be smaller. Figure 5 shows that for higher measurement heights the best-fitting parameter a_1 gets bigger and the value of $1/f_0$ is consequently lower.

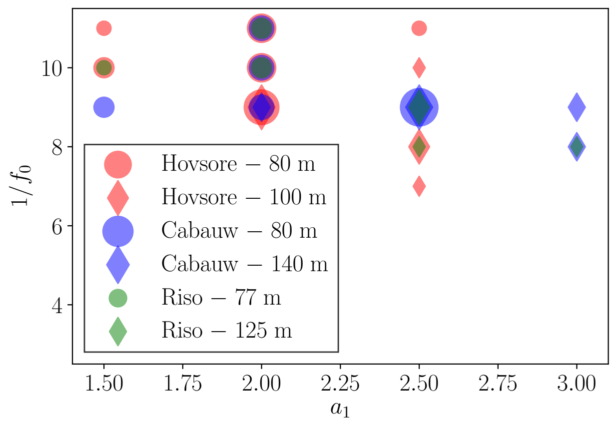

Figure 5. Scatter plot of best parameter combinations. The Hovsore results are shown in red, the Cabauw results in blue and the Risø results in green. The lower measurement heights are marked with a circle and the higher measurement heights with a $\diamond$. The size of the markers indicates if there are multiple cases with the same best parameter combination.

In Tables III, different years of measurements are shown. To distinguish between the years the mean (μ) and standard deviation (σ) of the measured data for that year are presented in the table. Results indicate that the parameter a_1 tends to be bigger if the mean wind speed is bigger. However, more analysis on more data is needed to confirm the connection between a_1 and the mean of the wind speed.

It can be concluded from Tables III and Figure 5 that a good value for the a_1 parameter is $2 \cdot 10^{-4}$ and that the $1/f_0$ parameter should be selected in the range $9-11$ hours, for measurement heights of about 80 meters. For measurement heights of 100 meters and above a value of $a_1 = 2.5-3 \cdot 10^{-4}$ might be better suited while coupled with a lower $1/f_0$ value.

V. Conclusion

The paper deals with the modelling of wind speed in the simulation tool CorRES. The wind speed models in CorRES are composed of reanalysis data and stochastic models. The paper considers the parameterisation of the stochastic part of the CorRES wind speed model while considering the contribution of the reanalysis data for short-term analysis of power systems including wind.

Three sets of measurement data are considered in the paper for different measurement heights, locations and years. The best-fitting parameters are found to be dependent on the measurement height, year and location. However, for the measurement height of about 80 meters the best-fitting parameters are found to be in agreement between the three locations.

Acknowledgment

The authors would like to thank DTU Wind Energy for providing access to meteorological data from the RODEO on-line database (rodeo.dtu.dk).

This work is supported by the Science Foundation Ireland, by funding G. M. Jónsdóttir and F. Milano under project AMPSAS, Investigator Programme, Grant No. SFI/15/IA/3074.

Matti and Poul acknowledge support from the NSON-DK (Danish Energy Agency, EUDP, grant 64018-0032; previously ForskEL) and PSfuture (La Cour Fellowship, DTU Wind Energy) projects.

References

[1] M. Sarkar, M. J. Koivisto, M. Altin, and P. E. Sørensen, "Impact of power fluctuations in reactive power capability of wind power plants," in *Cigre Aalborg 2019: International Symposium*, 2019.

[2] T. Souxes, I.-M. Granitsas, and C. Vournas, "Effect of stochasticity on voltage stability support provided by wind farms: Application to the Hellenic interconnected system," *Electric Power Systems Research*, vol. 170, pp. 48–56, 2019.

[3] M. Koivisto, K. Das, F. Guo, P. Sørensen, E. Nuño, N. Cutululis, and P. Maule, "Using time series simulation tools for assessing the effects of variable renewable energy generation on power and energy systems," *Wiley Interdisciplinary Reviews: Energy and Environment*, vol. 8, no. 3, p. e329, 2019.

[4] W. C. Skamarock, J. B. Klemp, J. Dudhia, D. O. Gill, D. M. Barker, W. Wang, and J. G. Powers, "A description of the Advanced Research WRF version 3. NCAR Technical note-475+ STR," 2008.

[5] A. N. Hahmann, D. Rostkier-Edelstein, T. T. Warner, F. Vandenberghe, Y. Liu, R. Babarsky, and S. P. Swerdlin, "A reanalysis system for the generation of mesoscale climatographies," *Journal of Applied Meteorology and Climatology*, vol. 49, no. 5, pp. 954–972, 2010.

[6] X. G. Larsén, S. Ott, J. Badger, A. N. Hahmann, and J. Mann, "Recipes for correcting the impact of effective mesoscale resolution on the estimation of extreme winds," *Journal of Applied Meteorology and Climatology*, vol. 51, no. 3, pp. 521–533, 2012.

[7] P. Sørensen, N. A. Cutululis, A. Vigueras-Rodríguez, H. Madsen, P. Pinson, L. E. Jensen, J. Hjerrild, and M. Donovan, "Modelling of power fluctuations from large offshore wind farms," *Wind Energy: An International Journal for Progress and Applications in Wind Power Conversion Technology*, vol. 11, no. 1, pp. 29–43, 2008.

[8] E. Nuño, P. Maule, A. Hahmann, N. Cutululis, P. Sørensen, and I. Karagali, "Simulation of transcontinental wind and solar PV generation time series," *Renewable Energy*, vol. 118, pp. 425–436, 2018.

[9] DTU Online Meterological data (2019). [Online]. Available: http://rodeo.dtu.dk/

[10] Cesar, Cabauw Experimental Site for Atmospheric Research (2019). [Online]. Available: http://www.cesar-database.nl/

[11] X. G. Larsén, C. Vincent, and S. Larsen, "Spectral structure of mesoscale winds over the water," *Quarterly Journal of the Royal Meteorological Society*, vol. 139, no. 672, pp. 685–700, 2013.