

EUDP IEA Task 41

Deliverable 2.3: Report on suggested improvements for time series simulation tools when working with DW

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Summary:

This report reviews recent advancements in wind time series simulation methods. The focus is on the most important aspects related to modelling small-scale and distributed wind (DW). The report also suggests improvements to further enhance the tools' suitability to analysing DW.

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1. Introduction

This report reviews models, datasets and approaches used in simulating wind speed and generation time series. Such time series are needed to understand the weather dependent variability in wind generation [1]. Variability impacts both producers' revenues, especially when wind generation and electricity prices are correlated [2], and the power and energy systems, as more flexible systems are needed. There are some specific challenges related to modelling small-scale or distributed wind (DW), especially as many of the time series simulation models are applied in analysing large-scale wind power. The following reviews some key aspects and suggests some further improvements to the models.

2. Review of wind time series simulation

There are two main approaches for simulating wind time series: 1) stochastic simulation; and 2) basing the simulations on meteorological data. 2) is the most common approach, and it has benefits over 1), as discussed in [3]. The following review of methods is based on 2); however, it is argued that stochastic simulation has benefits when combined to meteorological data.

2.1 Reanalysis datasets

Often used reanalysis data sets for modelling wind time series include MERRA and MERRA-2 [9], ERA-Interim [5] and ERA5 [1]. The ERA5 reanalysis was shown to give more representative wind time series compared to MERRA-2 in [6]. The ERA5 spatial resolution is around 30 km, whereas regional models can reach a resolution of a few km [7], [8]. High resolution regional reanalysis (COSMO-REA2) was shown to perform well in France [7]; ERA5 was shown to also perform well, although with biases in mean wind speeds in mountainous regions. New European Wind Atlas mesoscale runs were shown to perform well in reducing bias in mean wind speed estimates [8].

Concluding from the literature, regional reanalysis data can be successfully used in simulating wind time series. However, they have limited geographical, and sometimes also temporal, availability. On the other hand, e.g., ERA5 reanalysis data are available globally for tens of years (<https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5>). ERA5 has been shown to be accurate in representing wind speeds over large geographical regions; however, with challenges in complex terrain [1], [7]. This challenge can be mitigated by using microscale data together with the reanalysis data, as discussed in the next section.

2.2 Microscale data

Microscale wind data are of high spatial resolution (higher than 1 km), but typically given as distributions [8]. Thus, they cannot be used directly to obtain wind time series. However, microscale wind information can be used to scale the reanalysis time series to provide higher resolution spatial information to the relatively coarse reanalysis datasets [1], [9]. This can be

especially important for DW, as simply interpolating from reanalysis data averages out most of the local terrain information. Microscale wind data are available globally from the Global Wind Atlas (GWA) (<https://globalwindatlas.info/>).

An example of the mean wind speed ratio between microscale and reanalysis data, here between GWA and ERA5, can be seen in Figure 1. The differences between the two are significant in mountainous areas, and in some coastal areas. Flat areas onshore show similar mean wind speed in GWA and ERA5.

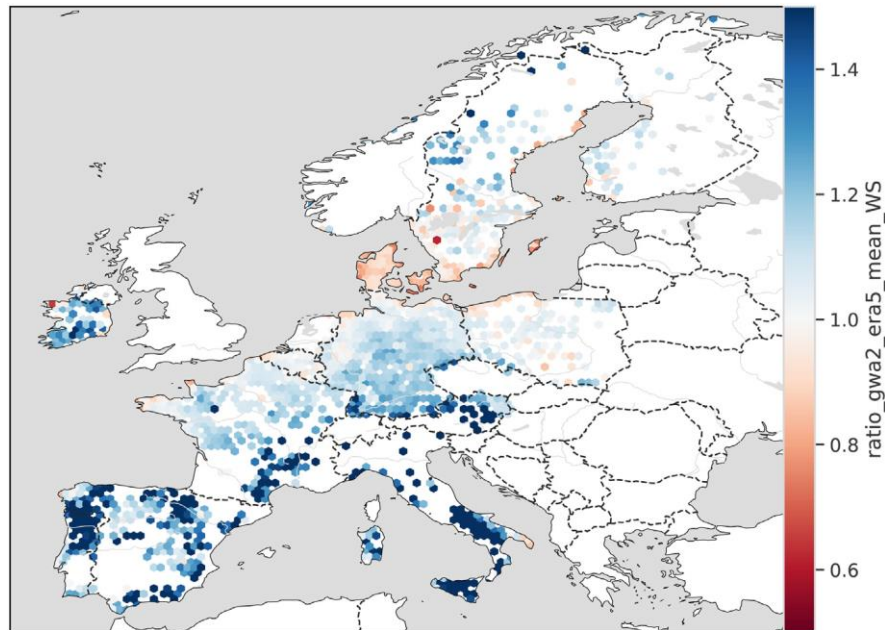


Figure 1. The ratio between mean wind speed of ERA5 and GWA, calculated for existing wind power plants in 2018. The figure is from [1].

2.3 Transformation to power generation

If a power plant consists of multiple turbines, it is important to consider wake losses [10]. This may be less important for DW, if plants are small, but should nevertheless be considered. A machine learning wake loss model was implemented in [1] to obtain approximate wake loss information even when information about the exact turbine locations is not available.

The importance of wind technology (hub height, turbine type) selection for different wind resources is highlighted in [2]. Different technology selection provides the optimal levelized cost of energy (LCOE) at different sites with different wind resource. The time series information allows optimisation considering also variable electricity price, including correlation with wind generation, which can favour different technology than considering only LCOE [2].

2.4 Sub-hourly resolution

The reanalysis data are usually hourly, or sometimes with 30 min resolution [1]. And even if the data are with hourly resolution, they may still lack hourly variability information [11]. However,

some applications may need higher than hourly resolution: e.g., in a microgrid with DW, sub-hourly ramps may be crucial when assessing the if the system can be always in balance.

While higher temporal resolution meteorological simulations may be available, they can be computationally expensive. Another option is to add the missing high frequency information to the reanalysis data using stochastic simulation [10], [11]. An example of adding stochastic fluctuations on reanalysis data is shown in Figure 1. It has been shown that calibrated multivariate stochastic simulation methods, combined with hourly reanalysis data, can represent the sub-hourly wind speed and generation ramps [11], [10]. The resulting time series can then be used in assessing, e.g., how a power system balancing can manage the sub-hourly variability in wind generation.

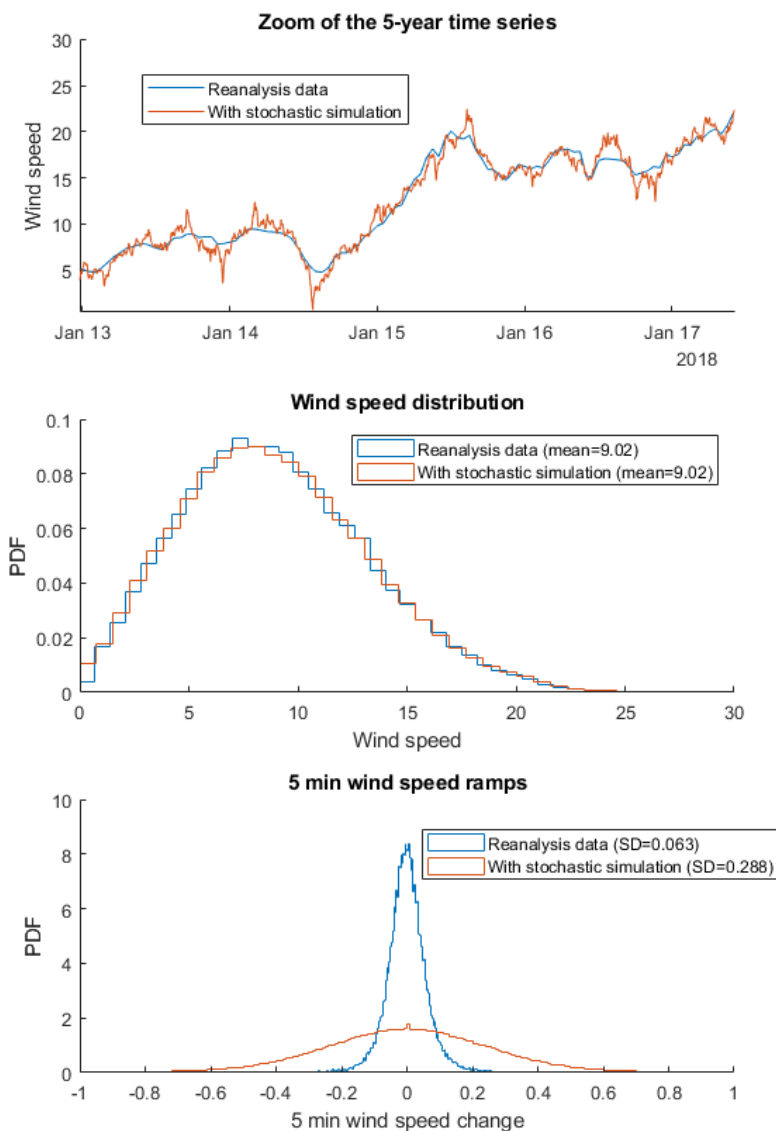


Figure 2. Linearly interpolated 5 min wind speed data from hourly reanalysis data without (blue) and with stochastic simulation (red). The stochastic simulation does not significantly change the wind speed distribution, but increases the high frequency variability (e.g., 5 min ramps).

2.5 Forecast errors

Wind generation forecast errors can be important, e.g., to understand the balancing needed when moving from day-ahead spot market towards the actual operation of the power system. As day-ahead market bids are based on day-ahead forecasts, they have forecast errors which need to be solved via intra-day or balancing markets, which operate closer to the actual operation of the system and have thus generally lower forecast errors.

The actual operation of the day-ahead markets towards balancing markets and finally to the operation of reserves (usually by transmission system operators) is done based on operational forecast methods. However, time series simulation can be used to analyse what kind of forecast errors we may see in the future [12], [13], and how to, e.g., size reserves to manage them.

3. Suggested improvements to the time series simulation models

The following sections highlight some developments which can further improve time series simulation models for DW.

3.1 High-resolution wind direction modelling

The scaling method to use microscale wind information with reanalysis time series data described in Section 2.2 does not consider wind direction. Also, the high frequency stochastic simulation method presented in Section 2.4 does not consider sub-hourly wind direction change. As DW needs very localised information, also the wind direction information on local level may need to be used to supplement the coarse reanalysis data.

3.2 Combination to local plant-level information

The methods described in Sections 2.2 and 2.4 to supplement the coarse reanalysis time series with higher resolution information are mainly applied for large-scale analyses. To be suitable for DW, an efficient way to bring the information to a more local turbine-level may be needed. The time series simulation methods could thus be incorporated in models such as WAsP (<https://www.wasp.dk/>) to bring time series analyses as part of standard wind farm assessment.

3.3 Validation with DW

The studies mentioned in Sections 2.2 and 2.4 are focused on large-scale. Although in principle the presented methods should have high-enough resolution to be applicable on DW, the validation on the more local level is lacking.

3.4 Combining with solar time series

If DW is used in in the same plant (hybrid plants) or in the same power system with solar power, it is important to ensure that the correlations between wind and solar are properly modelled. Considering reanalysis data, the same reanalysis time series should be used to analyse both wind and solar. The stochastic simulation methods presented in Section 2.4 and the forecast simulation methods described in Section 2.5 are often designed either for wind or solar separately, and thus may not consider the correlations between them properly. More focus

should be put to make sure that all aspects of the time series methods fully consider the dependencies between wind and solar.

4. Conclusions

Several developments have increased the accuracy of wind time series simulation. Modern reanalysis datasets are well suited for modelling wind generation time series. When supplementing them with high resolution microscale wind data and stochastic simulation, the resulting simulations have both high temporal and spatial resolution. High resolution reanalysis data can also be used to achieve higher resolution, however, with additional computational costs.

However, most literature has validated the wind time series simulation methods on the large-scale. More local-scale studies relevant for DW would help in validating the methods for DW usage. The modelling should also consider the correlations between wind and solar if both resources are utilised. It can be beneficial to have time series simulation as part of standard plant-level analysis software.

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We have more than 240 staff members of which approximately 60 are PhD students. Research is conducted within nine research programmes organized into three main topics: Wind energy systems, Wind turbine technology and Basics for wind energy.

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