High-Resolution Wind Profiles for Dynamic Wind Turbine Modeling Using Reanalysis Weather Models and Spectral Wind Models

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***Abstract*—The integration of renewable energy sources such as wind power into the electrical grid presents unique challenges due to their intermittent and stochastic nature. To address these challenges, this study presents a methodology for generating turbulent wind profiles with high temporal resolution by combining low-resolution reanalysis weather models with high-resolution spectral wind models. The generated profiles serve as inputs for dynamic generator models of wind turbines, enabling more accurate simulation of their operational behavior. The proposed methodology is demonstrated using the Copernicus European Regional ReAnalysis (CERRA) dataset combined with the National Renewable Energy Laboratory's (NREL) TurbSim spectral wind model. The resulting turbulent wind profiles provide improved fidelity in capturing wind generation dynamics, leading to more realistic simulations. A case study comparing the impact of linearly interpolated and turbulent wind profiles on the wind turbine performance is presented, showcasing the potential of the methodology for grid stability and energy storage planning.**

***Index Terms*—dynamic simulation, wind generation, reanalysis weather models, spectral wind models**

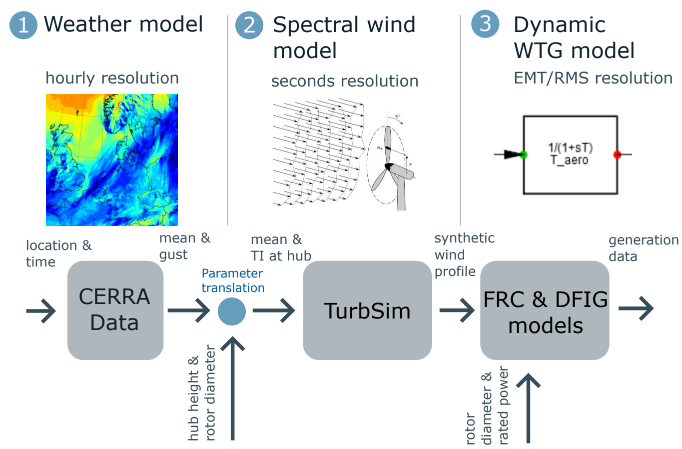

Fig. 1: Overview diagram of the proposed methodology, applying a parameter translation between CERRA weather model [1] and TurbSim wind model [2] to generate dynamic wind profiles suitable for EMT and RMS simulations.

I. Introduction

The transition to renewable energy sources is reshaping global energy systems. Wind energy, in particular, has become a key component of the energy mix. However, accurate modeling of Wind Turbine Generators (WTGs) requires high-resolution power generation data, which is often unavailable. This paper introduces a novel approach to generating realistic high-resolution wind profiles by integrating reanalysis weather models with spectral wind models as input data for dynamic WTG models. The motivation for this work lies in the need for improved WTG models, which play a crucial role in applications such as grid integration and stability studies.

Real and representative generation profiles of WTGs are often not publicly available due to confidentiality restrictions of WTG manufacturers and/or operators. To overcome this issue, researchers can draw upon weather models to predict weather conditions that directly influence the generation of WTGs. Such weather models are for example the Copernicus European Regional ReAnalysis (CERRA) [1] model, which this paper focuses on, with a spatial resolution of 5.5x5.5 km and temporal resolution of one hour. The problem of using such weather data directly as the input to WTG models lies in the low temporal resolution of such datasets. These models offer mean and maximum wind speed values over specified time intervals. However, wind as a fluid dynamic flow exhibits significant instability, leading to phenomena such as wind gusts and lulls that fluctuate on finer timescales around the average wind speed.

Consider an exemplary scenario where the average wind speed of the weather model is 5 m/s over one hour. One possible unsteady wind speed profile might have a wind speed of 8 m/s for the first 30 minutes and 2 m/s for the next 30 minutes, yielding an hourly average of 5 m/s. Another possible steady profile maintains a constant wind speed of 5 m/s for the entire hour.

The energy generated by these profiles is compared using the power curve of a representative 2 MW class wind turbine. At 8 m/s, the turbine output is around 850 kW, so over 30 minutes it produces 425 kWh. However, at 2 m/s — below the cut-in speed — no energy is produced in the second half-hour, resulting in a total of 425 kWh for the full hour. In contrast, a steady 5 m/s wind speed corresponds to about 200 kW, yielding 200 kWh over the full hour. Despite both profiles having the same average wind speed of 5 m/s, the unsteady profile produces more than twice as much energy.

The reason for the discrepancy between unsteady and steady wind profiles lies in the nonlinear power curve of WTGs. In general, the power output P of a WTG can be approximated by the following piecewise function [3],

$$P(v) = \begin{cases} 0, & v < v_{\mathrm{ci}}, \\ \frac{1}{2}\, C_p\, \rho\, A\, v^3, & v_{\mathrm{ci}} \leq v < v_{\mathrm{r}}, \\ P_{\mathrm{rated}}, & v_{\mathrm{r}} \leq v \leq v_{\mathrm{co}}, \\ 0, & v > v_{\mathrm{co}}, \end{cases} \tag{1}$$

where v is the wind speed in m/s, v_{ci}, v_{r}, and v_{co} are the cut-in, rated and cut-out wind speeds. The dimensionless aerodynamic power coefficient C_p for modern WTGs often approaches 0.5, which is near the theoretical Betz limit of approximately 0.59. Further, ρ is the air density in kg/m^3, and A is the swept rotor area (defined by the rotor diameter) in m^2. Below the cut-in speed ($v < v_{\mathrm{ci}}$), the turbine produces no power. Between cut-in and rated speeds, power increases cubically with wind speed. From the rated speed up to the cut-out speed ($v \leq v_{\mathrm{co}}$), the turbine generates a constant rated power P_{rated} and above the cut-out speed, it again produces no power for safety reasons. Notably, averaging wind speed linearly — as it is done in the calculation of mean wind speeds — does not capture the cubic influence on power, so short periods of higher wind speeds (gusts) can yield disproportionately large energy outputs compared to longer periods of moderate wind speeds, leading to significant discrepancies if only mean wind speeds are considered as also observed in the example given in Table I.

Beyond the differences in total energy output, the profiles have important implications for grid integration. In the example a constant 5 m/s profile can sustain a 200 kW load continuously without additional storage, whereas the unsteady profile would over-generate in the first 30 minutes and under-generate in the last 30 minutes, requiring an energy storage system to smoothen supply. [1]

TABLE I: Comparison of two simple wind speed profiles and the resulting difference in energy production

Profile	Time (min)	Wind Speed (m/s)	WTG Power (kW)	Energy (kWh)
Profile 1 (unsteady)	30	8	850	425
	30	2	0	0
			Total	**425**
Profile 2 (steady)	60	5	200	200
			Total	**200**

Note: Both profiles have a 1-hr mean wind speed of 5 m/s, yet produce different total energy. The values are chosen exemplary for a 2 MW class WTG.

A third implication arises from the dynamics of WTG itself. The aerodynamic power coefficient C_p is dependent on the tip-speed ratio λ, characterized by typical $\lambda - \mathrm{C_p}-$curves, which indicate that each turbine has an optimal tip-speed ratio λ, where C_p is maximized, allowing for the highest aerodynamic efficiency [3]. Maintaining this optimal ratio is crucial for maximizing power extraction, and it is the primary objective of Maximum Power Tracking (MPT) controller. The dynamic of this controller is limited due to the rotational inertia of the rotor which must be accelerated or de-accelerated to achieve the new optimal tip-speed ratio λ. Additionally, also the pitch angle adjustment speed is limited by mechanical constraints. This makes the dynamics of this control loop slower than typical wind gusts and causes the extracted energy to be below the theoretic maximum for steady wind speeds as described by Tang et al. [4].

Contribution: Our contribution to this field is to combine data from weather models with high-resolution spectral wind models to address the limitations of low temporal resolution datasets and capture the dynamic behavior of wind fluctuations more accurately. By integrating reanalysis weather models such as the Copernicus European Regional ReAnalysis (CERRA) with spectral wind simulation tools like NREL's TurbSim [2], we generate synthetic wind speed profiles that better represent the inherent variability of wind conditions at finer timescales. This approach allows for improved modeling of the dynamic response of WTGs, enabling more precise assessments of power fluctuations, grid stability, and storage requirements. By applying our proposed methodology, plausible generation models can be synthesized for generic locations as illustrated in Figure 1.

The proposed methodology is validated by a case study that evaluates the impact of different temporal resolutions on wind turbine performance. The study highlights how turbulent wind profiles improve the accuracy of power output simulations and enable better estimation of energy storage needs for grid integration.

[1] Though illustrated on wind energy, similar implications apply to solar irradiance modeling for PV production, especially when evaluating self-sufficiency in buildings or off-grid systems.

II. RELATED WORK

The modeling of wind generation variability is crucial for power system planning and stability analysis. Various methods have been explored to address the challenge of capturing wind speed fluctuations at different temporal and spatial scales, including stochastic simulations and meteorological reanalysis techniques.

The study by Olauson et al. [5] presents a hybrid approach to simulate intra-hourly wind power fluctuations by combining hourly meteorological model outputs with stochastic models of wind power generation derived in the frequency domain from measured power fluctuations. While this approach effectively captures aggregated wind power fluctuations at a regional level, it is not well-suited for representing the fluctuations of individual wind turbine generators (WTGs), which exhibit unique dynamic responses to varying wind conditions. Similar, Koivisto et al. [6] proposed a methodology that combines meteorological reanalysis data with stochastic simulations to model wind generation variability. Their approach utilizes the CorRES tool, which integrates reanalysis data from the Weather Research and Forecasting (WRF) model with stochastic simulation to account for high-frequency wind fluctuations. While their methodology effectively improves temporal resolution and models short-term fluctuations, it also primarily focuses on large-scale regional aggregation and does not explicitly consider the dynamic response of single WTGs. In contrast, our approach extends those works by incorporating high-resolution synthetic wind profiles as inputs to dynamic WTG models, enabling accurate assessment of power fluctuations at the individual wind turbine level.

Zárate-Miñano et al. [7] introduced new wind speed models based on stochastic differential equations (SDEs) assuming a Ornstein–Uhlenbeck process. These models effectively capture short-term wind variability while maintaining the statistical properties of wind speed. However, they furthermore assume stationarity and lack consideration of long-term seasonal variations. Our method addresses these limitations by integrating reanalysis data to capture long-term trends and supplementing them with spectral wind models for high-frequency fluctuations.

In summary, while previous research has contributed valuable methods for wind speed modeling or generation modeling on the regional level, our approach advances the field by combining reanalysis weather data with spectral wind models and explicitly incorporating individual dynamic WTG models.

III. METHODS

A. Modeling of dynamic WTG generation profiles

The methodology consists of three key components as illustrated in Figure 1. First, reanalysis weather data (1) provides a baseline representation of large-scale wind patterns with relatively coarse temporal resolution. These datasets capture the long-term climatology and synoptic-scale weather patterns but lack the ability to resolve short-term variations crucial for dynamic turbine simulations. Second, a spectral wind model (2) is applied to synthetically generate high-frequency wind fluctuations that reflect the turbulent nature of wind. As a third component these synthetic high-resolution wind profiles are feed into WTG models (3) to consider the dynamic of the WTG itself. This combination enhances the accuracy of WTG simulations by bridging the gap between low-resolution climate models and the fast dynamics of turbine operations.

1) Weather Model: The first step involves acquiring hourly wind speed and gust data for a desired location from the CERRA reanalysis dataset. CERRA provides wind speed values at multiple heights, with the 100 m level being selected as it is close to the hub height of WTGs, on a spatial resolution of 5.5 km x 5.5 km.

To adapt the CERRA data for use in the subsequent spectral wind model, a parameter translation is required. First, the mean wind speed is extrapolated to the specific hub height using the well-established power law [3], [8],

$$u(z) = u(z_{ref}) \left(\frac{z}{z_{ref}} \right)^{\alpha}, \tag{2}$$

where $u(z)$ is the wind speed in m/s at height z and $u(z_{ref})$ is the wind speed at reference height z_{ref}, equal to 100 m for the data obtained from the CERRA dataset, α is the dimensionless power law exponent and empirically determined. A typical assumption for α is 0.143 (equivalent to 1/7), which provides a practical approximation for neutral atmospheric stability as recommended by the IEC61400 standard [9].

Secondly, the spectral wind model requires the turbulence intensity TI at hub height as an input. The turbulence intensity can be derived from the available gust speed data, which represents the highest wind speed during a 1-hour period.

The connecting link between turbulence intensity and gust wind speed is the gust factor G which can be derived in two ways. First, it expresses the ratio between the gust wind speed and the mean wind speed by [8],

$$G(z) = \frac{u_{gust}(z)}{u_{mean}(z)}. \tag{3}$$

Alternatively, it is defined as a statistical property via the turbulence intensity over [9],

$$G(z) = 1 + aTI(z)^b \ln \left(\frac{T}{t_g} \right), \tag{4}$$

where a and b are empirical constants obtained from field measurements. The averaging period T represents the interval over which the mean wind speed is calculated (1 h or 3600 s), and t_g is the gust duration of 3 seconds, as defined by the CERRA dataset. This link between Equation (3) and Equation (4) allows to calculate the turbulence intensity TI as

$$TI(z) = \left(\frac{\frac{u_{gust}(z)}{u_{mean}(z)} - 1}{a \ln \left(\frac{T}{t_g} \right)} \right)^{1/b}. \tag{5}$$

For the parameters we choose $a = 0.50$ and $b = 1.00$, as suggested by Ishizaki [10].

2) Spectral Wind Model: The turbulent wind profile generation is performed using the NREL TurbSim software [2]. TurbSim is an established tool, commonly used also in the certification process of WTGs, and generates spatially and temporally correlated turbulent wind fields based on the following key input parameters:

- Mean wind speed at hub height – derived from CERRA data using the power law as given by Equation (2)
- Turbulence intensity – estimated from CERRA wind gust data by Equation (5)
- Spectral Model – IEC Kaimal to ensure realistic representation of wind turbulence [2]
- Wind field dimensions matching rotor diameter
- Simulation period and time step

To reduce the effect of parameter jumps given to the spectral wind model, the hourly input data is first linearly interpolated at 5 minute intervals. For those intervals a dynamic wind profile is then calculated by TurbSim.

3) Dynamic Wind Turbine Models: The generated wind profiles with higher temporal resolution are used as inputs to dynamic WTG models implemented in DIgSILENT PowerFactory. Two — by far market dominating — WTG types are considered [3]:

- **Type 3 – Doubly-Fed Induction Generator (DFIG):** A partially rated power converter controls the rotor current, enabling flexible reactive power control. We adapted the ”Wind Farm” example provided by Digsilent as part of the PowerFactory examples.
- **Type 4 – Full Converter Wind Turbine (FRC):** A full-scale converter decouples the generator from the grid, allowing for better grid compliance and fault ride-through capabilities. This model is based on dynamic model provided by Pertl [11].

The parameters of both models are adjusted to show comparable dynamics using methodologies based on estimating the rotor inertia by the rotor diameter as described by Tang [4] and Morren [12] for a 3 MW class wind turbine.

B. Validation and Case Study

To showcase the difference the dynamics has to grid integration studies, a system with energy storage is considered. The system is based on the Digisilent application example called ”BESS” from [13] and modified by adding a WTG type 4 model as previously described, connecting it to the same bus bar as the battery converter, as shown in Figure 2. In addition, the generation of the power plant used in the original model is limited, so that it only stabilizes the system in case more power generation is required.

IV. Results

A. Synthetic Profile Generation

1) Wind Speed Profiles: Synthetic wind speed profiles based on our novel methodology are generated for a hub height of 149 m for three distinct representative days: a windy, a calm, and a stormy day. Exemplarily, the profile from the windy day is shown in Figure 3.

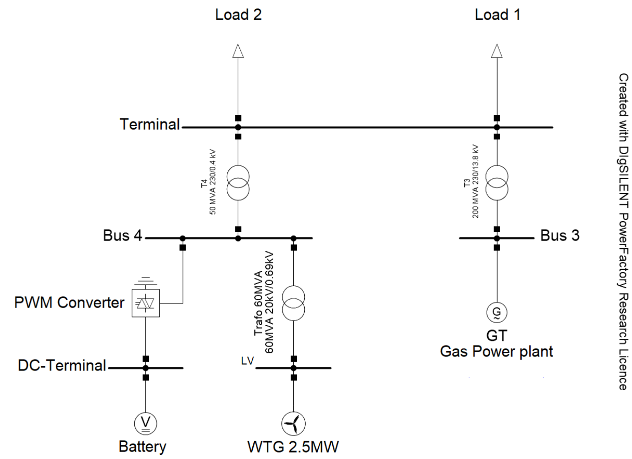

Fig. 2: PowerFactory model from [13] modified to include a type 4 wind turbine

The synthetic profile shows notable fluctuations above and below the linear interpolated profile, better representing the variable nature of wind speeds. Despite the fluctuations, the moving average over a 1-hour period of the synthetic wind profile stays remarkably close to the linear interpolated CERRA profile. The mean absolute error has value of 0.54 m/s, indicating that the synthetic wind speeds are in average slightly too high. It is visible that this deviation is highest when the hourly data changes significantly, indicating that the discrepancy might arise from the way parameter transitions are handled. Another indicator how well the synthetic profile shares the same statistical parameters as the input data is the gust wind speed, which can also be calculated from the synthetic profile by taking the moving maximal wind speed over a period of 1 h. The synthetic profile stays notable below the gust wind speed with a mean error of 2.2 m/s. This discrepancy can partly be explained by the fact that with 5 s resolution, the wind gust duration t_g is not equal to the one used in the CERRA dataset. An overview of those benachmarks for the chosen representative days is given in Table II.

TABLE II: Wind Profile Comparison

Cond.	**Date**	$\bar{u}$ (m/s)	Δu (m/s)	$\Delta u_{\%}$ (%)	Δu_{gust} (m/s)	$\Delta u_{gust\%}$ (%)
Stormy	10.02.23	16.4	0.87	5.3	5.83	15.8
Windy	14.10.23	8.6	0.54	6.3	2.20	13.7
Calm	24.10.23	3.0	0.43	14.3	0.91	21.3

Comparison of absolute Δu and relative $\Delta u_{\%}$ errors, for mean wind speeds and gust wind speeds under different weather conditions.

2) Power Generation Profiles: To evaluate the impact of high-resolution synthetic wind profiles compared to linearly interpolated profiles, the power output of a wind turbine using both profiles is compared and visible in Figure 4 over a one-day period.

The left plot in Figure 4 shows the power output derived

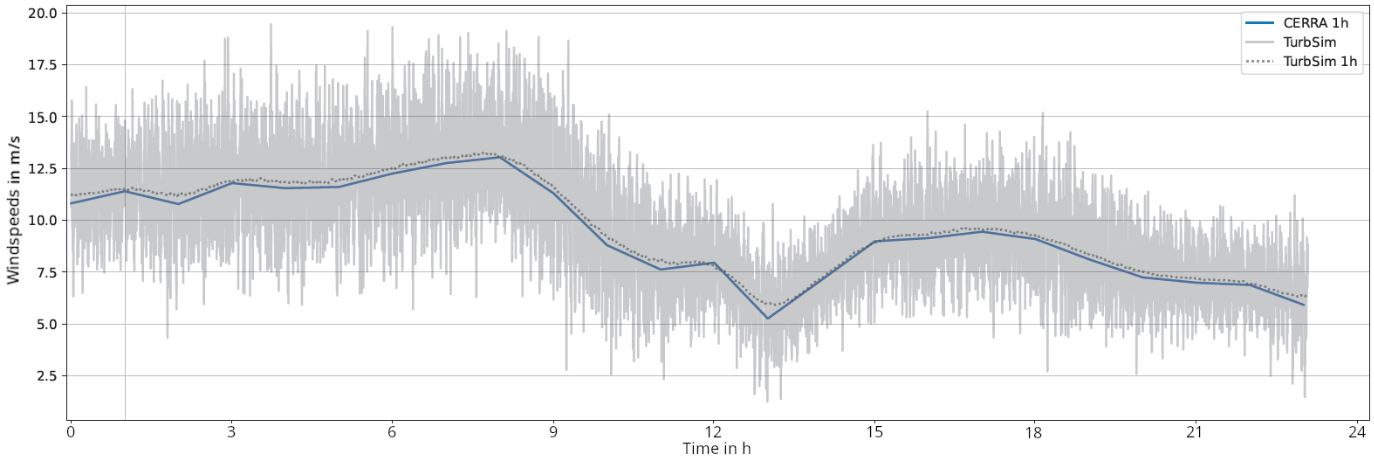

Fig. 3: Comparison of wind speed profiles for a windy day, October 14, 2023, at the location of the wind farm "Harthäuser Wald." The blue curve represents a wind profile obtained through linear interpolation of the hourly CERRA data. The solid gray curve illustrates the synthetic wind profile generated using our methodology at a 5-second resolution. The dotted line indicates the moving average over a 1-hour period of the synthetic wind profile.

from the turbulent synthetic wind profile generated using TurbSim, which exhibits significant fluctuations due to the turbulent wind speeds. The right plot represents the power generation based on a linearly interpolated wind profile derived from the hourly CERRA data, resulting in a smoother and less variable power curve.

Despite both profiles having the same hourly mean wind speed of 8.6 m/s, the turbulent profile captures the short-term wind speed variations that are critical in determining the real power output of a wind turbine. These fluctuations lead to periods of higher instantaneous wind speeds, resulting in higher power output due to the cubic dependence of genereated power on wind speed, as described in Equation (1). Conversely, periods of lower wind speeds are visible as sharp declines in power generation. Also visible is clipping, when the gust wind speed exceeds the power rating of the WTG. Qualitatively speaking, the turbulent profile is more realistic and resembles the profiles for example described by Tang et al. [4].

For operational planning, this has several implications. In this case, the turbulent profile results in a lower total energy yield compared to the linear profile, as the wind turbine experiences brief periods of higher wind speeds, that exceed the power rating, but also sharp declines in lulls that lower the energy production overall. For days with lower wind speeds, where no clipping occurs, the opposite holds as due to the cubic relation between wind speed and generated power, the gusts dominate to contribute significantly more power. Regarding storage requirements, the turbulent profile introduces sharp declines in generation, necessitating energy storage solutions to smoothen supply and ensure stable power delivery.

B. Study Case – Battery Energy Storage System (BESS)

The results from the BESS simulation highlight the significant impact of wind profile resolution on energy storage and utilization, see Figure 5. When using the synthetic turbulent wind profile, the BESS experiences more frequent charging and discharging cycles compared to a linearly interpolated profile.

The turbulent profile results in 2.03 MWh of energy being fed into the system, whereas the linearly interpolated profile results in only 0.83 MWh, leading to an absolute error of 1.2 MWh and a percentage deviation of 59.1%.

Further, the maximum State Of Charge (SOC) reached with the turbulent profile is 0.75, significantly lower than the 0.95 achieved with the interpolated profile. The final SOC after discharge is 0 for the turbulent profile and 0.3 for the linear profile, highlighting a greater reliance on the battery in the turbulent scenario. Also, the battery exhibits a more realistic battery cycling behavior, with both charging and discharging cycles occurring within the first 1000 s. Conversely, with the linear profile, the battery only charges during the initial low-load phase and discharges continuously after the load increased.

V. Conclusions & Outlook

In conclusion, we show that the use of high-resolution turbulent wind profiles significantly enhances the accuracy of power output estimation, supporting better planning for renewable integration and system stability assessments. For this, we introduce a novel methodology for generating turbulent wind profiles with high temporal resolution by combining low-resolution reanalysis weather models with high-resolution spectral wind models. Overall, the synthetic wind profiles demonstrate a good agreement with the reference data, with mean differences within acceptable limits. However, the observed underestimation of wind gusts indicates potential areas for improvement in the parameter translation for the spectral model, for example by adjusting the empirical parameters a and b in Equation (5).

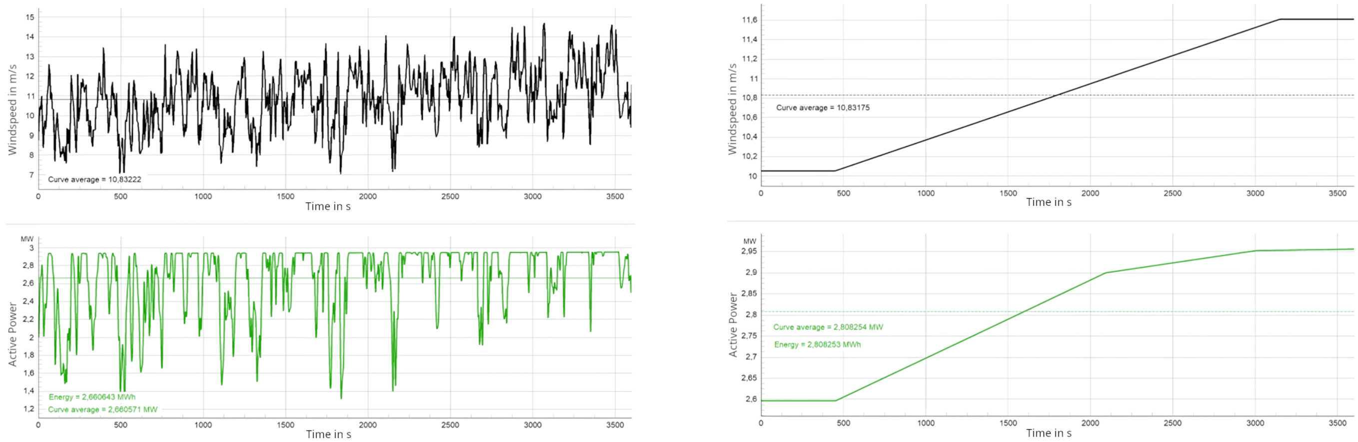

Fig. 4: Comparison of wind turbine power output over a shared one-hour period. Left) High-resolution synthetic wind profiles generated with our methodology. Right) Linearly interpolated wind profiles derived from hourly CERRA data. The turbulent profile captures short-term fluctuations, leading to periods of power clipping when wind speeds exceed the turbine's rated capacity, as well as sharp declines due to lulls. In contrast, the interpolated profile results in a smoother power output, which may overestimate total energy yield on days with frequent clipping and underestimate it on days with lower wind speeds. These differences highlight the impact of profile resolution on energy estimation and storage requirements.

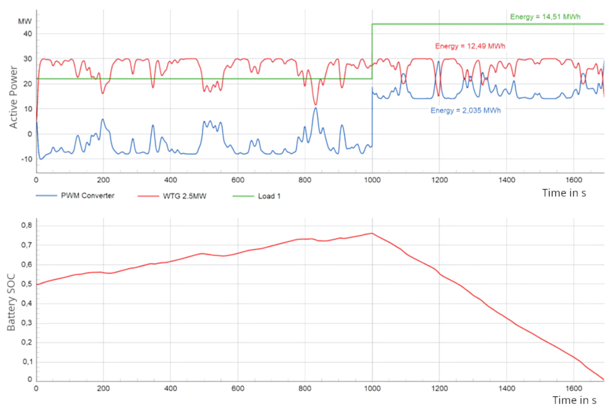

Fig. 5: Top) Power response of the wind turbine, the BESS and the load to a turbulent wind speed profile. Bottom) State of charge (SOC) of the battery

Future work may focus on refining spectral wind models to further reduce discrepancies observed in gust estimation and improve overall profile accuracy or to integrate different weather models.

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References

[1] S. Schimanke, M. Ridal, P. Le Moigne, L. Berggren, P. Undén, R. Randriamampianina, U. Andrea, E. Bazile, A. Bertelsen, P. Brousseau, P. Dahlgren, Edvinsson L., A. El Said, M. Glinton, S. Hopsch, L. Isaksson, R. Mladek, E. Olsson, A. Verrelle, and Z.Q. Wang Z.Q., "CERRA sub-daily regional reanalysis data for Europe on single levels from 1984 to present," 2021. [Online]. Available: https://doi.org/10.24381/cds.622a565a

[2] B. J. Jonkman, "Turbsim User's Guide: Version 1.50," National Renewable Energy Lab. (NREL), Golden, CO (United States), Tech. Rep. NREL/TP-500-46198, Sep. 2009. [Online]. Available: https://doi.org/10.2172/965520

[3] T. Ackermann, *Wind Power In Power Systems*. Chichester, West Sussex, England ; Hoboken, NJ: John Wiley & Sons Ltd, 2005.

[4] C. Tang, M. Pathmanathan, W. L. Soong, and N. Ertugrul, "Effects of Inertia on Dynamic Performance of Wind Turbines," *Australasian Universities Power Engineering Conference*, 2008.

[5] J. Olauson, M. Bergkvist, and J. Ryden, "Simulating intra-hourly wind power fluctuations on a power system level," *Wind Energy*, vol. 20, no. 6, 2017.

[6] M. Koivisto, G. M. Jónsdóttir, P. Sørensen, K. Plakas, and N. Cutululis, "Combination of meteorological reanalysis data and stochastic simulation for modelling wind generation variability," *Renewable Energy*, vol. 159, pp. 991–999, Oct. 2020.

[7] R. Zárate-Miñano, M. Anghel, and F. Milano, "Continuous wind speed models based on stochastic differential equations," *Applied Energy*, vol. 104, pp. 42–49, Apr. 2013.

[8] S. Emeis, *Wind Energy Meteorology*, ser. Green Energy and Technology. Cham: Springer International Publishing, 2018.

[9] B. Li, Q. Yang, and J. Yang, "Wind characteristics near ground in south-eastern coast area of China based on field measurement," *Geomatics, Natural Hazards and Risk*, vol. 7, no. sup1, pp. 57–69, May 2016, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/19475705.2016.1181459.

[10] H. Ishizaki, "Wind profiles, turbulence intensities and gust factors for design in typhoon-prone regions," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 13, no. 1, pp. 55–66, Dec. 1983.

[11] M. Pertl, "Doubly-fed induction generator wind turbine model," Apr. 2021. [Online]. Available: https://thesmartinsights.com/pitch-controlled-variable-speed-doubly-fed-induction-generator-dfig-wind-turbine-model-in-digsilent-powerfactory/

[12] J. Morren, J. Pierik, and S. W. H. de Haan, "Inertial response of variable speed wind turbines," *Electric Power Systems Research*, vol. 76, no. 11, pp. 980–987, Jul. 2006.

[13] DIgSILENT GmbH, "BESS ApplicationExample," 2020. [Online]. Available: https://www.digsilent.de/en/faq-reader-powerfactory/do-you-have-an-application-example-for-a-battery-energy-storage-system-bess.html