



Brief Communication: Actuator Disk Models reproduce Actuator Line Model power and thrust fluctuation statistics in wind farm simulations

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Abstract. Actuator-disk models (ADMs) are widely used in wind-farm simulations, yet their ability to reproduce power and thrust fluctuations relative to actuator-line models (ALMs) has not been validated. Using JHTDB-Wind simulation data, we compare ADM and ALM turbine-response statistics under three atmospheric conditions within a diurnal cycle. ADM power and thrust are reconstructed from disk-averaged velocity and evaluated using time series, power spectra, alongside fluctuation and increment distributions. Results show that ADM captures temporal, spectral, and statistical behavior of the ALM at timescales slower than the rotor frequency. Results support ADM as an efficient tool for predicting turbine-response variability in large wind-farm simulations.

1 Introduction

Wind-turbine power and thrust fluctuate because turbines operate in turbulent atmospheric flows. In wind farms these quantities are also influenced by the wakes of upstream turbines. Power fluctuations are of great interest as they determine the unsteady electrical output of a turbine or wind farm and therefore affect grid integration, storage requirements, and control strategies (Apt, 2007; Bandi, 2017). Thrust fluctuations determine the unsteady force exerted by the turbine on the flow and are directly related to wake dynamics, aerodynamic loading, fatigue, and turbine lifetime (Kosović et al., 2026). Accurately predicting both quantities is therefore important for wind-farm modeling, turbine-load assessment, as well as control-oriented design and operational studies.

Large-eddy simulations (LES) of wind farms require turbine representations that balance accuracy and cost. A relatively high-fidelity approach is the actuator-line model (ALM), in which rotating blades are represented by a large number of actuator points on a line along the rotating blade span (Shen et al., 2012; Martínez-Tossas et al., 2015). Lift and drag forces at each point are computed from local LES velocities and projected onto the LES grid (Martínez-Tossas et al., 2015), with appropriate models accounting for unresolved shed vorticity physics (Martínez-Tossas et al., 2024). The turbine power is obtained from



the aerodynamic torque, $T(t)$, as

$$P(t) = T(t) \Omega(t), \quad (1)$$

where $\Omega(t)$ is the rotor angular velocity. ALM include blade rotation, azimuthal sampling, and radial loading variations, and are therefore typically considered suitable for assessing power and thrust fluctuations from LES (Martínez-Tossas et al., 2015)

In order to reduce the computational burden, many wind-farm LES studies instead use actuator-disk model (ADM), in which the turbine is represented as a permeable disk that extracts momentum and energy from the resolved flow (Jiménez et al., 2010). ADM can typically be applied in LES with coarser meshes than ALM (see (Martínez-Tossas et al., 2024), however). The relevant inflow quantity for ADM is the disk-averaged velocity,

$$U_D(t) = \frac{1}{A} \int_{A_D} \mathbf{u}(\mathbf{x}, t) \cdot \mathbf{n} dA, \quad (2)$$

where $\mathbf{u}(\mathbf{x}, t)$ is the fluid velocity resolved in LES. This velocity depends on the three dimensional position $\mathbf{x}$ and time t , A_D is the swept area perpendicular to the airflow, $A = \pi D^2/4$ is the rotor area, and $\mathbf{n}$ is the rotor-normal direction. The corresponding ADM calculated values of thrust and power are

$$F_T(t) = \frac{1}{2} \rho A C'_T U_D^2(t), \quad (3)$$

and

$$P(t) = \frac{1}{2} \rho A C'_P U_D^3(t). \quad (4)$$

Here, C'_T and C'_P are the “local” thrust and power coefficients defined with respect to the disk-averaged velocity (Meyers and Meneveau, 2010) rather than the nominally undisturbed upstream velocity. This formulation is attractive for wind-farm simulations because U_D is directly available from the resolved flow, so it obviates the need for ambiguous definitions of upstream velocity for turbines operating in wakes (Calaf et al., 2010; Meyers and Meneveau, 2010).

Comparisons of wake and flow-field quantities, including mean wake profiles, turbulence intensity, grid-resolution effects, and force-projection choices (Porté-Agel et al., 2011; Martínez-Tossas et al., 2015; Stevens et al., 2018) have shown that ADM and ALM can produce similar intermediate and far-wake flow statistics and, under controlled conditions, comparable mean power predictions. Prior analyses of ADM-generated power fluctuations (Stevens and Meneveau, 2014; Singh and Alam, 2024; Liu and Stevens, 2026; Tobin et al., 2019) assumed that the ADM generated realistic predictions of power and thrust temporal fluctuations but this assumption has not been thoroughly tested. Therefore, it remains unclear whether ADM-based estimates can reproduce the temporal, spectral, and statistical structure of ALM power and thrust fluctuations. The purpose of this brief communication is to describe detailed comparisons between ADM and ALM predictions of fluctuation statistics.

Using the JHTDB-Wind diurnal-cycle LES database (Xiao et al., 2025), which provides both time-resolved flow fields and ALM turbine-response data, we construct ADM estimates of power and thrust using disk-averaged velocity. We compare these estimates with the corresponding ALM signals based on detailed blade-level time and position-dependent force information.



Our analysis uses time series, power spectral densities, and probability density functions (PDFs) of fluctuations and power fluctuation increments to assess whether the ADM captures not only the mean response, but also the dominant fluctuation behavior of turbine power and thrust.

55 2 JHTDB-Wind Diurnal Cycle Database

The present analysis uses the JHTDB-Wind small wind farm diurnal-cycle dataset described in detail in (Xiao et al., 2025). This dataset consists of both time-resolved flow fields and turbine-level ALM quantities from LES of an 8-turbine wind farm operating over a full 24-hour diurnal cycle. Figure 1 illustrates the database flow domain, an instantaneous hub-height flow field, and turbine power signals provided by the database. This dataset is well suited for the present study because the resolved
60 velocity fields can be used to construct the ADM input variables, while the ALM turbine power and thrust provide the reference signals. The simulated wind farm contains 8 NREL-5MW arranged in 4 streamwise rows and 2 spanwise columns, with streamwise and spanwise spacings of $7D$ and $5D$, respectively.

The turbines have diameter $D = 126$ m and hub height $z_h = 90$ m. The flow is driven by a prescribed geostrophic wind, and the simulation includes Coriolis forcing, wind veer, and time-varying solar surface heating, leading to varying atmospheric
65 stability that follows a typical diurnal cycle. During the ALM simulation, the turbines yaw to align with the mean hub-height inflow direction from the precursor domain. The turbines operate in below-rated, region-II conditions at an approximately optimal fixed tip-speed ratio at all times, so the rotor angular velocity varies in time with the local incoming velocity.

For the present comparison, we use the stored three-dimensional velocity fields, available every 0.5 s, to compute yaw-aligned disk-averaged velocity signals at the rotor plane. The ADM power and thrust estimates are then constructed from
70 the disk-averaged velocity and compared directly with the corresponding ALM turbine-response signals. Turbine-level ALM data, including power, thrust, and rotor angular velocity, are available for each turbine at $\Delta t = 0.05$ s. This setup enables a comparison of ADM and ALM power and thrust fluctuations across different temporal windows of the diurnal cycle.

3 Power and Thrust Fluctuations estimated by Disk-averaged Velocities

The analysis focuses on turbine 7 (see Figure 1a), which is located in the last row and experiences wake-affected inflow.
75 To evaluate the ADM performance under different atmospheric conditions, we consider three distinct temporal windows of the diurnal cycle (shown as shaded regions in Figure 1c): 15:00–18:00, representative of late-afternoon convective conditions; 00:00–03:00, representative of nocturnal stable conditions; and 10:00–13:00, representative of post-morning-transition daytime conditions. A single turbine-based comparison allows us to compare ADM and ALM fluctuation predictions across these
80 varying conditions without introducing the additional complexity of aggregating signals across multiple turbines. Since farm-level power and thrust are obtained from the superposition of individual turbine responses, verifying accurate recovery of the fluctuation behavior of representative single turbines is sufficient for evaluating the extent to which ADM-based predictions match those of the more accurate ALM simulations.

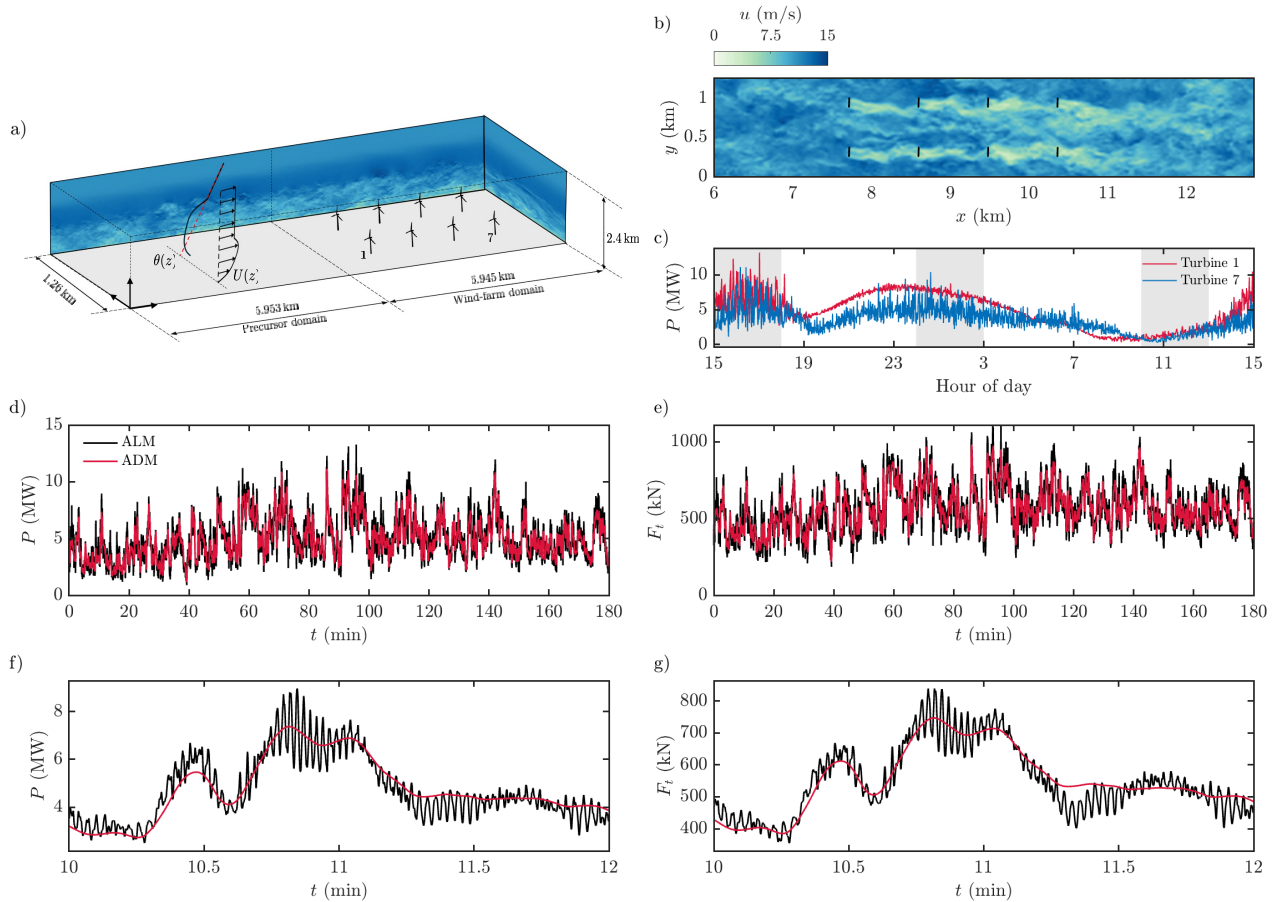


Figure 1. a) Schematic of the domain in which flow data is stored during an entire 24 diurnal cycle. Color contours represent a snapshot of streamwise turbulent velocity at 18:00. b) Instantaneous contours of the streamwise velocity at hub height at 18:00, viewed from above. Black lines are the turbines. c) Turbine power signal over the full 24-h cycle (red line for a turbine in first row and blue for a waked turbine in last row); shaded regions indicate the three temporal windows considered in this study. Plots d) through g) show the comparison of ALM and ADM turbine-response signals for turbine 7 during the 15:00–18:00 window. Panels (d) and (e) show the time signals of turbine 7 power and thrust, respectively. Panels (f) and (g) show corresponding two-minute excerpts, highlighting the short-time-scale variability in the power and thrust signals.

To construct the ADM thrust and power predictions, we first compute the disk-averaged rotor-normal velocity from the time-resolved flow fields. The flow-field data used in this study are queried from JHTDB-wind with `getData(...)` at the yaw-rotated rotor-disk sampling locations and stored flow-field times. Since the turbines are yawed to ensure that the veer angle is zero at hub height, the rotor disk is not fixed in the y - z plane. Instead, at each time t , the disk is rotated by the instantaneous turbine yaw angle $\gamma(t)$, and the averaged velocity is taken along the rotor-normal direction. The disk-averaged velocity is



computed as

$$U_D(t) = \frac{1}{A} \int_{A_D} [u(\mathbf{x}, t) \cos \gamma(t) + v(\mathbf{x}, t) \sin \gamma(t)] dA, \quad (5)$$

90 where $A_D(\gamma)$ the yaw-rotated swept area perpendicular to the airflow, and u and v are the streamwise and spanwise velocity components from LES data, respectively. In practice, the integral is evaluated by sampling the velocity over points contained within a circular disk of radius $D/2$ centered at the turbine hub (using spatial spline interpolation afforded by JHTDB-wind querying capabilities) and averaging the rotor-normal velocity over those points at each stored flow-field time. Because the ALM rotor angular velocity $\Omega(t)$ is determined from the axial velocity sampled one grid cell ($\Delta = 18.375$ m) upstream of
 95 the rotor, we evaluate the yaw-rotated disk-averaged velocity at the same location for consistency. We then apply a sharp low-pass spectral filter to the disk-averaged velocity, using the mean turbine rotational frequency in each temporal window as the cutoff. The cutoff frequencies are $f = 0.203$ Hz for 15:00–18:00, $f = 0.202$ Hz for 00:00–03:00, and $f = 0.124$ Hz for 10:00–13:00. This filtering restricts the ADM predictions to variability on time scales longer than the rotor-rotation time scale, consistent with the rotor-disk-averaged nature of the ADM. The corresponding turbine-level ALM quantities, including yaw,
 100 power, thrust, and rotor angular velocity time-series, are obtained from JHTDB-wind using `getTurbineData(...)` calls (Xiao et al., 2025).

The ADM predictions of power and thrust are respectively computed using Eqs. (4) and (3). The coefficients C'_P and C'_T are first estimated independently for each temporal window of the diurnal cycle by requiring the mean ADM response to match the corresponding ALM response, with $C'_P = \overline{P_L} / (0.5 \rho A \overline{U_D^3})$ and $C'_T = \overline{F_{T,L}} / (0.5 \rho A \overline{U_D^2})$. Here, $\overline{P_L}$ and $\overline{F_{T,L}}$ are the time-
 105 averaged ALM power and thrust, respectively. The coefficients obtained for each region are then averaged to define a single pair of values used throughout the analysis. This procedure yields $C'_T = 1.263$ and $C'_P = 1.460$. These values are close to those predicted by classical actuator-disk momentum theory, for which $C'_T = C'_P = 4a/(1-a)$; for a representative induction factor $a = 0.25$, corresponding to $C'_T = C'_P \simeq 1.33$ (Stevens and Meneveau, 2014; Meyers and Meneveau, 2010).

3.1 Power and Thrust Time Signals

110 Figures 1d through 1g compare the ALM and ADM power and thrust time signals for turbine 7 during the 15:00–18:00 window. The ALM signals exhibit pronounced temporal variability, with fluctuations occurring both over the full window and over shorter time scales of a few minutes. The ADM estimates capture the dominant trends in both power and thrust, including the main low-frequency variations, while attenuating part of the short-time-scale variability that occurs on the time-scale of blade rotation (a few seconds). This attenuation is expected because the disk-averaging and temporal filtering reduces
 115 velocity fluctuations that are not coherent over the rotor area and eliminates the blade rotational flow sampling that is at higher frequency.

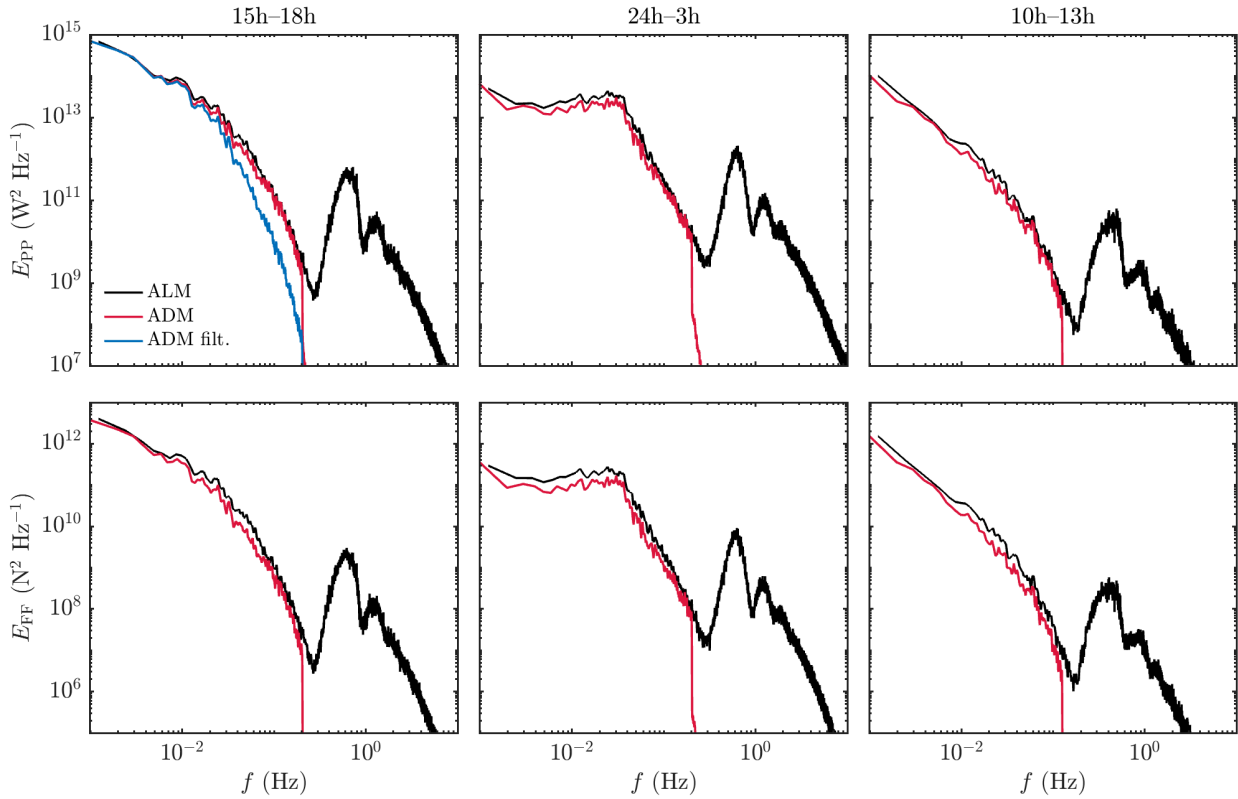


Figure 2. Power spectral densities of turbine #7 power and thrust fluctuations for the ALM (black line) and ADM (red line) signals. The top row shows the PSDs of power fluctuations, E_{PP} , and the bottom row shows the PSDs of thrust fluctuations, E_{FF} . Columns correspond to the three temporal windows considered: 15:00–18:00, 00:00–03:00, and 10:00–13:00.

3.2 Power Spectral Density of Power and Thrust Fluctuations

We next compare the ALM and ADM power and thrust fluctuations using their power-spectra densities (PSDs). Fluctuations are defined by subtracting the temporal mean, e.g., $P'(t) = P(t) - \bar{P}$ and $F'_T(t) = F_T(t) - \bar{F}_T$. The PSDs are estimated using Welch's method within each three-hour window. Because the ALM and ADM signals are sampled at different rates, $\Delta t = 0.05$ s and $\Delta t = 0.5$ s, respectively, we use different segment lengths: 2^{14} samples for the ALM and 2^{11} samples for the ADM. Both estimates use 75% overlap, a normalized Hanning window, and a Fourier-transform length equal to the segment length. These choices give comparable physical window durations for the ALM and ADM spectra, allowing comparison over the common range of resolved frequencies.

As can be seen in Figure 2, the PSDs obtained from the disk-averaged ADM estimates show good agreement with the ALM reference spectra for both power and thrust across the three temporal windows considered for frequencies below 0.25 Hz (i.e.



time-scales longer than a few seconds). Over a broad range of resolved frequencies, the ADM reproduces the main spectral energy content and captures the stability-dependent changes in spectral decay observed in the ALM signals. The ALM spectra also contain distinct peaks and harmonics associated with the blade-passing frequency, approximately $f \approx 0.5\text{--}0.65\text{ Hz}$, which arise from the periodic sampling of the turbulent inflow by the rotating blades. The overall spectral behaviors shown in Figure 2 vary substantially across the three temporal windows, reflecting changes in the turbulent inflow sampled by the turbines under different atmospheric stability conditions. In particular, differences in the spectral decay over the intermediate-frequency range suggest that the turbine response is influenced by the stability-dependent structure of the incoming turbulence.

3.3 Effect of Temporal Filtering

In actuator-disk simulations, the disk-averaged velocity used to compute turbine forcing is often temporally filtered after the spatial averaging over the rotor disk (Stevens et al., 2018; Goit and Meyers, 2015; Bempedelis et al., 2023). This filtering is commonly motivated as a way to reduce the influence of high-frequency oscillations in the instantaneous disk-averaged velocity. A commonly used one-sided exponential relaxation filter is given by

$$U_D^T(t) = \epsilon U_D(t) + (1 - \epsilon) U_D^T(t - \Delta t), \quad (6)$$

where $\epsilon = \Delta t / (\tau_f + \Delta t)$ is the relaxation coefficient, τ_f is the filter time scale, and U_D^T is the temporally filtered disk-averaged velocity. The choice of τ_f varies widely across studies, from short values such as $\tau_f = 0.2\text{ s}$ (Stevens et al., 2018) and $\tau_f = 5\text{ s}$ (Allaerts and Meyers, 2017; Goit and Meyers, 2015) to values proportional to boundary-layer scales (Calaf et al., 2010; Bempedelis et al., 2023).

Figure 2a shows the effect of applying this filter with $\tau_f = 5\text{ s}$ before computing the ADM response for the 15:00–18:00 temporal region. As expected, the filtering modifies the spectral content, reducing the amplitude of the fluctuations and steepening the spectral decay at intermediate frequencies. Similar behavior is observed across all temporal windows. Thus, temporal filtering can significantly affect ADM-based fluctuation estimates, and the filter time scale should be chosen carefully.

3.4 Probability Density Functions

We further assess the ability of the ADM to reproduce the statistical structure of the ALM fluctuations by comparing probability density functions (PDFs) of the power fluctuations and their temporal increments (Milan et al., 2013). Figure 3a shows the PDFs of the normalized power fluctuations. The ALM and ADM distributions agree closely across both the core and tails over their common sampled range, indicating that the ADM accurately reproduces the distribution of fluctuation amplitudes predicted by the ALM. Both distributions deviate from the Gaussian reference, reflecting the non-Gaussian character of the rotor-integrated turbine response. To further examine the temporal character of these fluctuations, Figure 3b compares PDFs of the normalized power fluctuation increments, $\delta P' = P'(t) - P'(t - \tau)$. Increment statistics have been used to characterize the intermittent, non-Gaussian nature of wind-turbine power fluctuations and the occurrence of rapid changes in power output (Milan et al., 2013). Here, the ALM increments are evaluated at $\tau = 0.5\text{ s}$, matching the sampling interval of the ADM signal. The ALM and ADM increment PDFs agree closely over most of the distribution, while a modest discrepancy is observed primarily in the



negative tail, where the ALM exhibits a higher probability of large negative increments. The PDFs of the thrust fluctuations
 160 and their increments exhibit behavior similar to that of the power fluctuations and are therefore omitted for brevity.

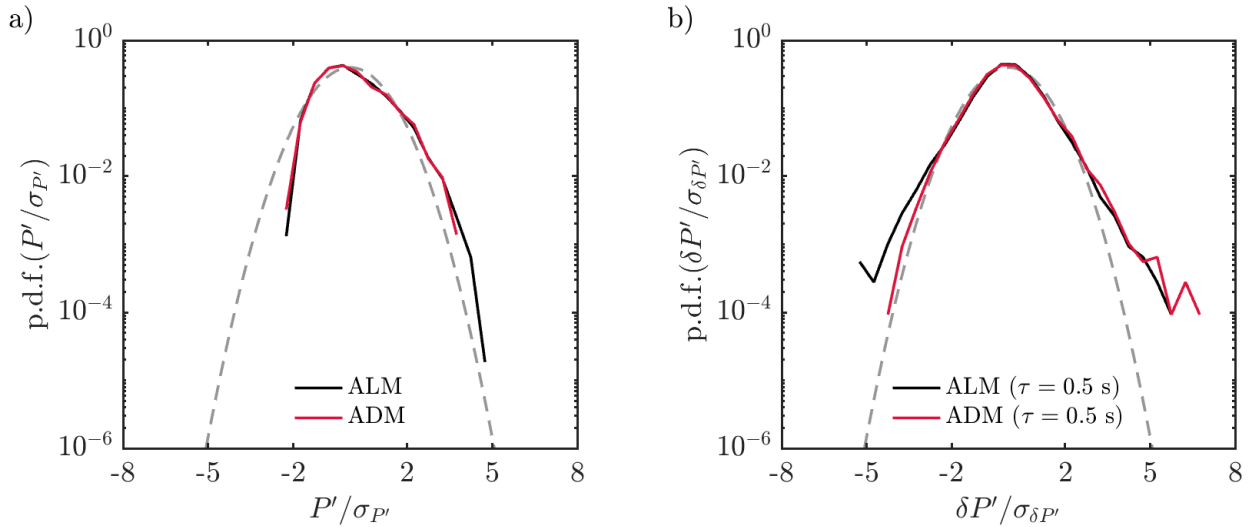


Figure 3. (a) Normalized probability density functions of power fluctuations for the ALM (black line) and ADM (red line) signals. (b) Probability density functions of normalized power fluctuation increments. The gray dashed line denotes a standard normal distribution with zero mean and unit variance.

4 Conclusions

We conclude that the ADM captures the dominant temporal, spectral, and statistical features of the ALM response at the relevant resolved flow-field time scales. In the time domain, it reproduces the main low-frequency variability while attenuating part of the short-time-scale fluctuations due to rotor-disk averaging and blade rotation. In the frequency domain, the ADM
 165 spectra agree well with the ALM spectra over the resolved range and reproduce the changes in spectral behavior across the diurnal cycle. Differences are most evident at high frequencies where ADM does not contain frequencies associated with blade rotation. The PDF comparisons further show that the ADM reproduces the core of the normalized power and thrust fluctuation distributions. Overall, these results support the use of ADM-based estimates for power and thrust fluctuations in large wind-farm simulations, provided that their temporal-resolution and filtering characteristics are taken into account appropriately.

170 *Data availability.* The wind farm data used in this study are available on the JHTDB-wind website at (<https://turbulence.idies.jhu.edu/datasets/windfarms/diurnalWindfarm>).



Author contributions. MA: data curation, formal analysis, methodology, software, visualization, writing (original draft preparation). DFG, CM: conceptualization, methodology, supervision. MA, DFG, CM: investigation, writing (review and editing). DFG, CM: funding acquisition.

175 *Competing interests.* The authors declare no competing interests

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