

Modeling Multiscale Atmospheric Interactions in Wind-Farm Power Spectra

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Wind-farm power spectra display distinct regimes that reflect how turbines collectively interact with the atmosphere. At low frequencies (approximately 10^{-4} Hz and below), turbine power outputs remain correlated, whereas at high frequencies (approximately 10^{-2} Hz and above), they decorrelate, smoothing wind-farm power fluctuations. Existing models typically capture only one end of this spectrum and lack a unified description across the transitional range (approximately 10^{-3} Hz). Here we introduce a dynamic sweeping model that predicts wind-farm power spectra across all scales. Slow mesoscale variations are represented as a time-dependent sweeping velocity that advects boundary-layer turbulence through the wind farm, while small-scale turbulence is modeled with use of the random sweeping framework. The model shows that the three spectral regimes originate from interactions between mesoscale weather systems, with timescales of about 15 min to hours, and microscale turbulence evolving over seconds to minutes. Large-eddy simulations and field data confirm that the model captures the mesoscale, transitional, and turbulence-dominated regimes, providing a physically consistent foundation for predicting wind power variability and supporting reliable grid integration.

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I. INTRODUCTION

Fluctuations in wind-farm power output arise from atmospheric turbulence spanning a wide range of spatial and temporal scales. Early field measurements revealed that at low frequencies, production of all turbines is strongly correlated, while at high frequencies their outputs behave largely independently [1]. The importance of understanding these variations has only grown as wind energy becomes a larger part of the power system. Quantifying how wind-farm power production varies across different frequencies is essential for estimating storage and reserve needs and for maintaining reliable grid operation [2–4].

To frame the problem, we distinguish between microscale and mesoscale atmospheric dynamics. Microscale turbulence is characterized by length scales below several kilometers and timescales of seconds to minutes [5–7], and governs interactions among neighboring turbines, whose outputs are only weakly correlated. Large-scale mesoscale weather patterns, spanning roughly 5–500 km and characterized by timescales of minutes to hours

[6,8–10], determine the low-frequency response of entire wind farms. Field-data analysis [11–16] showed that large-scale correlations decrease to about 0.5 only at separations of roughly 300 km, indicating that power fluctuations can be markedly reduced by aggregating production from wind farms influenced by different weather systems [17–19].

Industry practice typically relies on 10-min averages to assess wind resources and wind-farm performance. While useful, such averages omit sub-10-min variability, which is central to wind-power fluctuations. High-resolution measurements (Fig. 1) reveal three distinct regimes in wind-farm power spectra [20]: a low-frequency regime (below 2×10^{-4} Hz), where turbine outputs remain correlated; a high-frequency regime (above 3×10^{-3} Hz), where outputs decorrelate; and a transitional regime (2×10^{-4} – 3×10^{-3} Hz), where both influences overlap. This intermediate range is precisely where existing models provide no consistent explanation.

Existing approaches capture the low-frequency and high-frequency limits: mesoscale models such as the Weather Research and Forecasting Model capture low-frequency effects due to large-scale weather phenomena [21], while random sweeping models (RSMs) based on Taylor’s hypothesis [22–26] capture fast fluctuations. However, their interactions are not addressed. Here we propose a dynamic sweeping model that links wind power fluctuations across scales by treating slower variations as a time-dependent sweeping velocity that transports smaller-scale turbulence. This extension of the random

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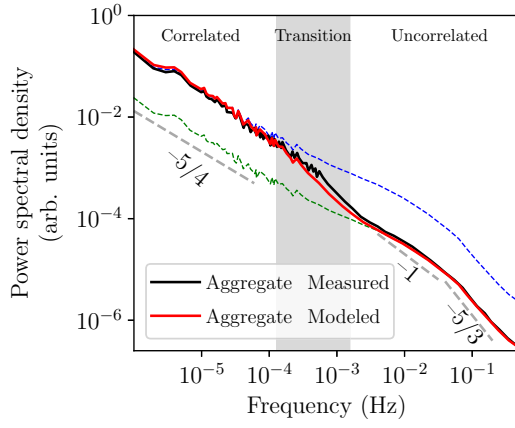


FIG. 1. Aggregate power spectrum measured at Mt Mercer wind farm (black line) [20], exhibiting the transition from highly coherent turbine output at low frequencies to less coherent high-frequency fluctuations. The red line indicates model predictions introduced in this study, with the interturbine coherence function modeled in Appendix C. The blue and green lines mark the upper and lower bounds of the wind-farm spectrum, obtained by combining the measured single-turbine spectrum with the assumption of fully correlated or completely uncorrelated turbine behavior.

sweeping concept provides a consistent explanation of the transitional regime. In Fig. 1 we show that the model can be used to reproduce measurements of the power fluctuations in Mt Mercer wind farm [20], where details of the comparisons are provided in Appendix C. In this work, the corresponding theory that is required to reproduce these wind-farm measurements is developed and validated against large-eddy simulations (LESs), as this allows the model to be developed and validated incrementally by having controlled and well-reproducible conditions.

In the remainder of this paper, we first introduce the theory in Sec. II. In Sec. III, we examine the coherence in power output between different turbine pairs in the wind farm, which reveals the physics of the three regimes. In Sec. IV, we discuss how these findings are reflected in the wind-farm power spectra. Conclusions are presented in Sec. V. Details of the simulations are provided in Appendix A, and the modeling of the atmospheric spectra is described in Appendixes B and C.

II. THEORY

In Secs. II A and II B, we describe how microscale atmospheric turbulence is captured with the random sweeping model and how low-frequency variability is represented with use of the dynamic sweeping approach.

A. Random sweeping models

The random sweeping hypothesis [23–28] assumes that the microscale turbulent velocity field u is advected by a uniform sweeping velocity v across the domain. The

advection of u is described by

$$\frac{\partial u}{\partial t} + v \frac{\partial u}{\partial x} = 0. \quad (1)$$

Using Taylor’s frozen-turbulence hypothesis [22], the model is based on three main assumptions: (1) the turbulent motion is considered “frozen” during advection; (2) wind turbines act as passive probes; and (3) the sweeping velocity can be decomposed as $v(t) = V + v'(t)$, where V denotes the time-averaged value of v , and v' represents the fluctuations. These fluctuations are assumed to follow a Gaussian distribution with zero mean and a standard deviation σ_v . Under steady wind conditions, variations in the sweeping velocity are attributed primarily to the large-scale boundary-layer structures; therefore, σ_v can be estimated from the variation of u [26,28,29].

We first consider two turbines aligned in a streamwise direction, with their separation denoted by Δ_x . The velocity coherence for this pair is defined as the ratio of the cross-spectrum between the two velocity signals measured by the turbines, Φ_{0,Δ_x} , to their autospectrum, denoted as Φ_{mi} . Taking the Fourier transform in time of Eq. (1), the random sweeping model predicts coherence by integrating over all possible values of v' [26,28]:

$$C_{\text{RSM}}(\omega) = \frac{\Phi_{0,\Delta_x}}{\Phi_{\text{mi}}} = \int_{-\infty}^{\infty} \exp\left(\frac{-i\omega\Delta_x}{V+v'}\right) f(v') dv', \quad (2)$$

where $f(v')$ denotes the probability density function of v' . With a Gaussian distribution for v' , the final form of the coherence function is obtained as

$$C_{\text{RSM}}(\omega) = \frac{1}{\sigma_v \sqrt{2\pi}} \int_{-\infty}^{\infty} \prod_{m=0}^{\infty} \exp\left[-\frac{i\omega\Delta_x}{V} \left(\frac{v'}{V}\right)^m\right] \times \exp\left(-\frac{1}{2} \left(\frac{v'}{\sigma_v}\right)^2\right) dv'. \quad (3)$$

The coherence function is expressed with respect to the angular frequency $\omega = 2\pi f$. The first exponential term represents the contribution of random fluctuations in the sweeping velocity, $1/(V+v')$, under a Taylor-expansion approximation with m terms, while the second exponential accounts for the Gaussian probability distribution of v' . For a detailed derivation, see Ref. [28]. Tobin and Chamorro [26] retained first two terms in Eq. (3) (up to $m = 1$) and proposed a linear random sweeping coherence model. This approximation is valid when the sweeping velocity fluctuations are small, i.e., $\sigma_v \ll V$, corresponding to nearly steady wind conditions. To incorporate large variations in v , resulting from mesoscale variations considered in this work, we retain higher-order terms (up to $m = 5$) to capture the nonlinear behavior.

Whereas Eq. (3) focuses on the convection of boundary-layer turbulence, parameters reflecting the impact of wind turbine operations are not included in the model. In practice, the wake turbulence influences wind power coherence greatly. Previous studies show that wind turbines convert the coherent structures in atmospheric turbulence to small-scale wake turbulence, which cannot correlate power output of wind turbines [26,28,29]. This loss of coherence is directly linked to the induction factor of the upstream turbines, as it determines the initial wake strength.

To model these effects, the coherence between turbine pairs in a wind farm takes the form [26]

$$C_{WF}(\omega) = C_0(a)C_{RSM}(\omega) \exp\left(-\frac{\Delta_y^2}{L_y^2}\right), \quad (4)$$

where $C_{RSM}(\omega)$ is the random sweeping coherence model [Eq. (3)], and the last term $\exp\left(-\frac{\Delta_y^2}{L_y^2}\right)$ describes the reduction in coherence due to spanwise separation, where Δ_y is the spanwise distance between turbine pairs and L_y is the spanwise coherence length [26,30]. Because the spanwise coherence length is much smaller than its stream-wise counterpart [31], the resulting spanwise coherence is inherently limited.

The wake-induced coherence reduction is represented by a multiplicative prefactor $C_0(a)$ smaller than 1, which is linked to the turbine induction factor a . Following Liu and Stevens [29], the prefactor C_0 is modeled as

$$C_0(a) = (1 - a + a^2)^N F(\Delta_x), \quad (5)$$

where N indicates the number of rows separating two turbines, with $N = 1$ representing consecutive turbine rows. The first term involving a accounts for turbine effects following the wake-deflection model of Liu and Stevens [29]. In this formulation, the flow is decomposed into two contributions: (1) A main-stream portion that is convected through the turbine rotor with volume fraction $1 - a$. The coherence is reduced by rotor operation and scales with velocity deficit (i.e., $C_0 \sim 1 - a$); (2) A portion with volume fraction a bypassing the turbine, which is assumed to be unaffected by the rotor and therefore has $C_0 = 1$. Combining these two contributions yields the prefactor $C_0 \sim (1 - a)^2 + a \times 1 = 1 - a + a^2$. The function $F(\Delta_x)$ models decoherence of undisturbed boundary layer turbulence over a distance Δ_x , which depends on atmospheric conditions. When turbine effects are absent ($a = 0$), F reduces to the constant C_0 . The value of F used in this work is obtained from wind-farm LESs with $a = 0$. In Fig. 2, we demonstrate that Eq. (5) captures the coherence pattern for wind-turbine power output for wind turbines separated by up to three rows. The LES study [29] further confirms that Eq. (5) broadly captures the turbine-induced coherence reduction in a wide range of induction factors and turbine spacings.

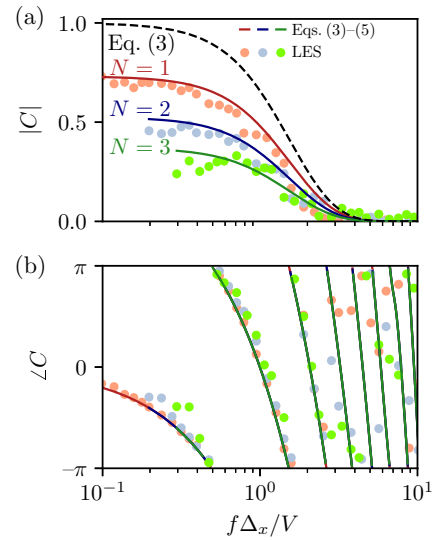


FIG. 2. Random sweeping model predictions of microscale power coherence of turbine pairs based on Eqs. (3)–(5) for separations from one row ($N = 1$) to three rows ($N = 3$). LES results are obtained with the same setup as in Sec. III ($C_T = 0.8$) with a constant hub-height inflow wind speed of 8 m/s.

B. The dynamic sweeping model

Random sweeping models assume steady conditions to predict coherence due to microscale atmospheric turbulence. In reality, microscale wind conditions are controlled by mesoscale weather systems, which impose low-frequency changes in wind speed and wind direction. Observations indicate that these mesoscale variations are mostly uncorrelated with microscale turbulence because large-scale weather systems extend over tens of kilometers, which effectively decouples them from small-scale turbulence in the atmosphere [8].

Therefore, for wind turbines within a wind farm, low-frequency wind speed variations can be viewed as a dynamic sweeping velocity that transports atmospheric turbulence past the turbines. Whereas the convection of microscale turbulence u is still consistently described by the random sweeping model using the statistical properties of sweeping velocity (V and σ_v), the variation in v contributes significantly to the power variation, which must be treated explicitly in the coherence analysis. We therefore consider the total wind speed variations $U(t)$ as the sum of a dynamic sweeping velocity $v(t)$ and the microscale atmospheric turbulence $u(t)$, i.e.,

$$U(t) = v(t) + u(t). \quad (6)$$

The Fourier transform for the time domain provides the coefficients in frequency space:

$$\hat{U}(\omega) = \hat{v}(\omega) + \hat{u}(\omega). \quad (7)$$

To quantify the relative contribution of mesoscale (Φ_{me}) and microscale (Φ_{mi}) components, we introduce a function, $r(\omega)$, defined by the ratio of their power spectral density:

$$r(\omega) = \frac{\Phi_{\text{me}}(\omega)}{\Phi_{\text{mi}}(\omega)} = \frac{\langle \hat{v} \hat{v}^* \rangle}{\langle \hat{u} \hat{u}^* \rangle}. \quad (8)$$

The full-scale wind turbine power spectrum Φ_{MM} can then be expressed as

$$\begin{aligned} \Phi_{\text{MM}} &= \langle \hat{U} \hat{U}^* \rangle = \langle (\hat{v} + \hat{u}) (\hat{v}^* + \hat{u}^*) \rangle \\ &= \langle \hat{v} \hat{v}^* \rangle + \langle \hat{v} \hat{u}^* \rangle + \langle \hat{v}^* \hat{u} \rangle + \langle \hat{u} \hat{u}^* \rangle \\ &= (r + 1) \Phi_{\text{mi}}. \end{aligned} \quad (9)$$

We assume that mesoscale and microscale variations are uncorrelated, which means $\hat{v}$ and $\hat{u}$ are statistically independent, and the cross-terms in Eq. (9) become zero.

Observations [8] indicate that mesoscale variability is approximately isotropic in the horizontal plane, with correlation strength depending primarily on separation distance rather than orientation. Therefore, unlike the random sweeping models, where streamwise and spanwise separations (Δ_x and Δ_y) are treated explicitly, we use a unified notion of interturbine distance, $\Delta = \sqrt{\Delta_x^2 + \Delta_y^2}$, in the dynamic sweeping framework. With this, the cross-spectrum can be expressed as

$$\begin{aligned} \Phi_{0,\Delta} &= \langle \hat{U}_\Delta \hat{U}_0^* \rangle \\ &= \langle (\hat{u}_\Delta + \hat{v}_\Delta) (\hat{u}_0^* + \hat{v}_0^*) \rangle \\ &= \langle \hat{u}_\Delta \hat{u}_0^* \rangle + \langle \hat{v}_\Delta \hat{v}_0^* \rangle, \end{aligned} \quad (10)$$

where the cross terms cancel due to the independence of $\hat{u}$ and $\hat{v}$. The first term on the right-hand side represents the microscale coherence, which is modeled with use of the random sweeping approach $\langle \hat{u}_\Delta \hat{u}_0^* \rangle = C_{\text{WF}} \Phi_{\text{mi}}$. The second term represents the mesoscale contribution, which we express as

$$\langle \hat{v}_\Delta \hat{v}_0^* \rangle = \zeta \Phi_{\text{me}} = \zeta r \Phi_{\text{mi}}. \quad (11)$$

Here we introduce the decoherence function ζ to model the potential decorrelation of mesoscale motions. Measurements indicate that wind turbine power correlations decrease exponentially with distance as $\exp(-\Delta/l_0)$, with a typical atmospheric integral length scale $l_0 \approx 300$ km [15]. Since typical wind farms are much smaller than l_0 , we set $\zeta = 1$ in our model for comparison with the LES results, implying a perfect mesoscale correlation within the wind farm. This assumption is justified, as for a typical wind-farm size Δ of 10 km, the correlation between the farthest turbines remains about 0.97. For wind farms covering significantly larger areas, a more general coherence

function ζ would be necessary to capture the decorrelation of mesoscale motions. An example of how the ζ model aligns with realistic scenarios is presented in Appendix C.

Combining Eqs. (9)–(11), we obtain the final expression of the dynamic sweeping coherence model:

$$C_{\text{DSM}} = \frac{\Phi_{0,\Delta}}{\Phi_{\text{MM}}} = \frac{\zeta r + C_{\text{WF}}}{r + 1}. \quad (12)$$

This expression connects mesoscale and microscale atmospheric effects through their relative strength, represented by r . For $r \gg 1$, low-frequency mesoscale variability dominates, and the coherence approaches the mesoscale coherence pattern ζ . For $r \ll 1$, microscale turbulence effects dominate, which are represented by the random sweeping model C_{WF} . In the intermediate range ($r \approx 1$), the flow transitions between the two regimes, with influences from both determining the coherence.

III. COHERENCE BETWEEN TURBINE PAIRS

To examine the coherence between turbine pairs, we perform LESs of a wind farm composed of DTU 10-MW turbines [32], with details of the simulation presented in Appendix A. The wind-farm layout comprises seven rows and four columns, with streamwise and spanwise spacings $S_x = 7$ and $S_y = 5$, respectively. We compare two scenarios: (1) zero thrust ($C_T = 0$, $a = 0$), where turbines passively record wind speed variations without generating wake turbulence, and (2) $C_T = 0.8$ ($a = 0.28$), where turbines operate below the rated wind speed to maximize power. Because $C_T = 0$ and $C_T = 0.8$ represent extreme cases, they provide insight into the upper and lower bounds of the coherence and wind-farm power spectra affected by turbine operation.

The coherence data are calculated from wind speed signals measured by each turbine, which equally reflect the power coherence under the context of constant C_T [28]. The dynamic wind speed signal v , described in Appendix B, is applied after the flow is fully developed. Disk velocity data with a time length of 120 h are collected, ensuring that the spectral calculations are statistically converged.

Figure 3 compares coherence spectra from LESs and the model for turbines separated by one and three rows. The spectra are averaged from the second row onward to reduce entrance effects [26,28,29]. For the $C_T = 0$ case, the model closely matches the LES results for atmospheric flow without wind turbine wakes. At low frequencies, mesoscale processes dominate, while at higher frequencies, microscale turbulence becomes the main driver. The model also reproduces the nonmonotonic behavior observed in the transitional regime, where peaks and troughs arise from the interference of frequencies. This occurs because the phase angle of the random sweeping model coherence shifts continuously with the frequency,

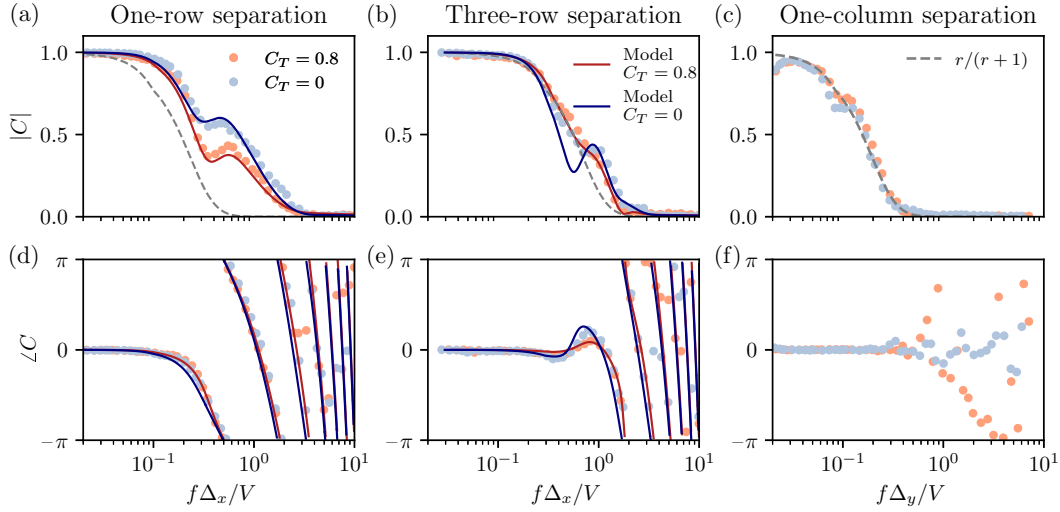


FIG. 3. Coherence spectra from LESs and the dynamic sweeping model [Eq. (12)] for turbine pairs operating with zero thrust ($C_T = 0$) and maximum thrust ($C_T = 0.8$). (a)–(c) Absolute coherence. (d)–(f) Phase angle. The labels in (a)–(c) apply to (a)–(f).

while the dynamic sweeping component remains real and positive. In Fig. 3(b), the LES data exhibit a less pronounced interference pattern than the model at intermediate frequencies. The error results mainly from a slight mismatch between $v(t)$ used in the analytical model and $v(t)$ realized in the LESs. Although the forcing approach in Eq. (A1) reproduces the target $v(t)$ with high accuracy, the coherence calculation is most sensitive to small residual deviations in the transition region, where the mismatch becomes noticeable.

Wind farm–atmosphere interactions reduce the mean wind speed within the wind farm relative to the undisturbed ambient flow. Accordingly, the random sweeping model should use an effective sweeping velocity smaller than the ambient wind speed to account for wind-farm effects. We represent this by setting $V = 0.85 \bar{v}$ for $C_T = 0.8$ in Eq. (3), on the basis of the LES results. Here $\bar{v}$ represents the mean value of the dynamic wind speed signal v , described in Appendix B. As the wake-induced turbulence does not contribute to the variation of sweeping velocity [26,28], we still consider the standard deviation of inflow velocity in the model. Figure 3 compares two scenarios, and shows that turbine wakes at $C_T = 0.8$ reduce coherence relative to the atmospheric flow case ($C_T = 0$), except at intermediate frequencies in Fig. 3(b), where frequency interference occurs.

Figure 3 also shows the mesoscale contribution $r/(r+1)$ (dashed lines); see Appendix B for details. The gap between the dashed lines and the overall coherence (red lines) highlights the contribution from microscale atmospheric turbulence. For turbine pairs separated by three rows, the microscale contribution becomes negligible as the LES results converge to the imposed mesoscale signal [Fig. 3(b)].

In the spanwise direction, no microscale coherence is observed, with the LES results fully overlapping with the imposed signal [Fig. 3(c)]. Consequently, at low frequencies, the turbine power output is correlated primarily with these large-scale variations, consistent with the mesoscale contribution $r/(r+1)$. The strong power correlation is consistent with field observations [15,20,33], and cannot be achieved through microscale turbulence [26,28]. At higher frequencies, microscale turbulence leads to sustained decoherence between turbines in the wind farm. Finally, we emphasize that the rapid phase angle changes at high frequencies have no physical impact, as the coherence is effectively zero in this range.

We further assess the dynamic sweeping model beyond the cases shown in this section by varying key parameters, including the sweeping-velocity signal (which affects the ratio function r), the turbine thrust coefficient, and the wind-farm layout. Across all test cases, the model remains in good agreement with the LES results, demonstrating the componentwise accuracy of the framework in predicting wind-farm power coherence across scales.

IV. WIND-FARM SPECTRA

To assess the model’s predictive ability for the overall wind-farm power spectrum, we analyze a 5×5 wind farm with turbines evenly spaced at $S_x = S_y = 5$. Three wind directions are considered (0° , 26° , and 45° ; see Fig. 4). In the 0° case, the streamwise spacing between consecutive turbines is smallest and wake effects in the wind farm are strongest. At 26° , 16 of the 36 turbines experience free inflow, increasing the overall wind-farm power output. The different wake effects are represented by $V = 0.85 \bar{v}$ (0°),

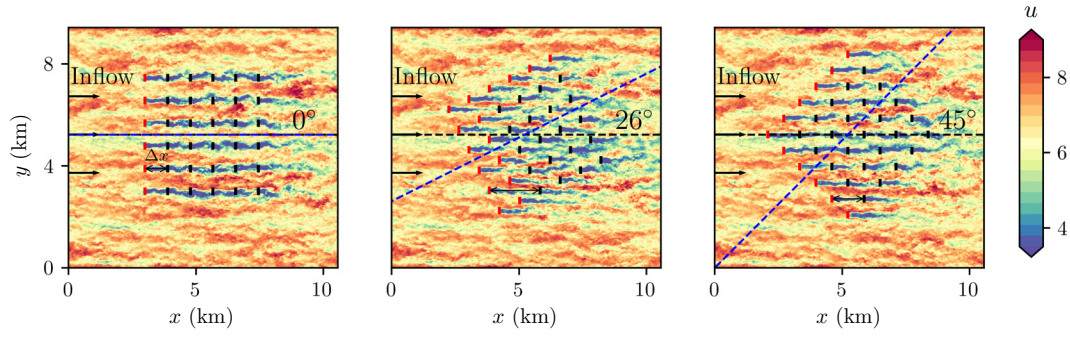


FIG. 4. Top view of the wind-farm configuration for different wind directions, with turbines receiving clean inflow highlighted in red. The dashed lines indicate the misalignment between the original wind-farm layout and the wind direction.

$V = 0.95\bar{v}$ (26°), and $V = 0.9\bar{v}$ (45°) in Eq. (3), as determined from LESs. Collectively, these scenarios illustrate how wind-farm performance varies with wind-farm layout.

Assuming the power output spectra of all turbines, Φ_1 , are statistically identical, the total wind-farm spectrum Φ_{WF} is given by

$$\Phi_{WF}(\omega) = A_{WF}(\omega)\Phi_1(\omega), \quad (13)$$

where the admittance function sums the real part of the coherence of all turbine pairs,

$$A_{WF}(\omega) = n + 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{Re}(C_{ij}(\omega)), \quad (14)$$

where C_{ij} is the coherence of power output between the i th and j th turbines in a wind farm with n turbines. The admittance function measures instantaneous power correlations within the wind farm, with $A_{WF} = n^2$ representing the fully correlated limit ($C_{ij} = 1$) and $A_{WF} = n$ representing the uncorrelated limit ($C_{ij} = 0$).

In Fig. 5, we show the resulting admittance function and wind-farm power spectrum predicted by the dynamic sweeping model via Eqs. (13) and (14). Compared with the LES results, the classical random sweeping model [Eqs. (3)–(5)] [29] underestimates the low-frequency content and therefore fails to capture the strongly correlated wind-farm power fluctuations associated with mesoscale variability. In contrast, the dynamic sweeping model we introduce here reproduces the observed trends well. For the admittance functions displayed in Fig. 5(a), low-frequency variations up to 10^{-3} Hz (about a 15-min timescale) remain highly coherent, consistent with the model prediction $A_{WF} = 36^2$.

At the low-frequency end, the LES results are slightly below the fully correlated limit predicted by the model. The remaining gap seems to depend mainly on the wind-farm layout. In particular, cases with smaller effective streamwise spacing, such as the 0° case, show larger deviations from the dynamic sweeping model than the 26°

case, where the spacing between consecutive downstream turbines is greater. Figure 3 shows that in low-frequency range, the LES-resulting coherence for $C_T = 0$ is closer to unity than for $C_T = 0.8$, which better matches the model prediction. As a result, the corresponding wind-farm admittance for the $C_T = 0$ case, which represents the inflow characteristics without turbine effects, also closely follows the model prediction in the representation in Fig. 5, although these results are not shown for brevity. Nevertheless, the agreement with LESs remains good in Fig. 5, which suggests that the low-frequency gap depends only weakly on wind-farm operation. Currently, this turbine effect is not captured in the dynamic sweeping framework. Explicitly accounting for wind-farm feedback at low frequencies could further increase the model's accuracy.

Above 2×10^{-2} Hz (approximately-1-min timescale), fluctuations become uncorrelated, and A_{WF} approaches its lower limit of $n = 36$. Layout effects appear in the intermediate region (5×10^{-3} – 2×10^{-2} Hz), where turbine spacing and alignment influence coherence between turbine power outputs [25,34]. The streamwise distance Δ_x between turbine rows determines the interference frequencies, while the number of downstream turbines controls their magnitude. The 0° layout, with perfect alignment, shows the strongest interference [34], whereas the 26° case shows the weakest and the 45° case lies in between. LES tends to amplify this signature relative to field data, since in practice the wind rarely remains perfectly aligned with the wind-farm layout for extended periods.

Figure 5(b) compares spectra from single turbines with spectra of the wind farm. From the wind-farm spectral density compared with the spectral density of individual turbines, we identify the correlated (less than approximately 10^{-3} Hz) and uncorrelated (greater than approximately 6×10^{-3} Hz) regimes and the transitional regime (10^{-3} – 6×10^{-3} Hz). Notably, the bounds of the different regimes are directly connected to the strength of mesoscale contributions, as illustrated in Fig. 6(b) in Appendix B. In the low-frequency region, the power spectral density of individual turbines depends on the wind

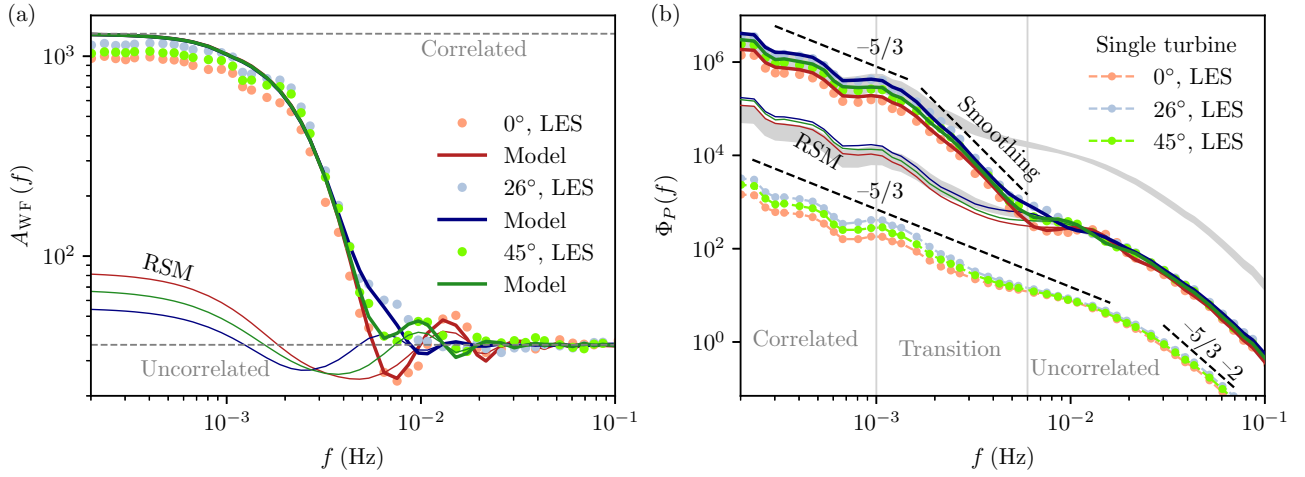


FIG. 5. Aggregate wind-farm power output from LESs (dotted lines) and dynamic sweeping model predictions by Eqs. (13) and (14) (solid lines). (a) Admittance function. (b) Power spectra of single turbines (lower curves) and the entire wind farm (upper curves). Results from classical random sweeping models [Eqs. (3)–(5)] [29] are included for comparison. The gray lines in (b) illustrate an extrapolation of the fully correlated and uncorrelated scenarios as a guide for the eye. The legends apply to (a),(b).

direction: the 26° case yields the highest power output and fluctuations, whereas the aligned 0° case produces the lowest. At these frequencies, the wind-farm spectrum follows the same scaling as the spectra of individual turbines because the admittance function remains close to its maximum value, indicating that the wind power is highly correlated inside the wind farm. This aligns with earlier findings that wind-farm power spectra follow a $f^{-5/3}$ scaling for timescales longer than 10 min [2,15,20].

Single-turbine spectra gradually converge in the transitional regime, suggesting that the influence of microscale turbulence is largely independent of the wind direction. Within the transitional regime, the wind-farm spectrum steepens, reflecting a loss of coherence between the power outputs of individual turbines. This spectral drop indicates that the wind-farm power smoothing effect is mainly due to the weak correlation of turbine output resulting from microscale processes at higher frequencies. At this region, the power fluctuations on the wind-farm level are sufficiently smoothed, and the spectral scaling returns to the same as that of individual turbines.

Additionally, we observe a sharper $f^{-5/3-2}$ scaling in turbine spectra at the high-frequency end, which is likely due to the filtering effects of the rotor. Studies suggest that this scaling arises at frequencies lower than 0.07 Hz (the rotor scale) [35,36], which is in agreement with our observations. We emphasize that observing the transitional and high-frequency regimes requires measurements with finer resolution than the standard 10-min averages typically used in wind energy practice. Nevertheless, wind-farm power production data, as shown in Fig. 1, have clearly evidenced these regimes.

V. CONCLUSIONS

This study introduces the dynamic sweeping model as a unified framework for predicting wind-farm power fluctuations across three distinct frequency regimes. The model integrates mesoscale atmospheric variability, microscale boundary-layer turbulence, and turbine-induced wakes into a single formulation. It shows that the three regimes arise from interactions between large-scale weather systems and small-scale atmospheric turbulence. In the low-frequency regime, turbine power fluctuations are associated with mesoscale weather variations and remain correlated with them. At high frequencies, microscale atmospheric turbulence dominates, and turbine outputs become uncorrelated. In the transitional range, spectral smoothing effects of wind-farm power outputs appear. LESs and field observations confirm that the model accurately captures the wind farm's response to transitions in the underlying multiscale turbulence and reproduces all three regimes. This provides a physically consistent basis for characterizing the power spectra of wind farms.

By enabling reliable modeling of wind-farm power spectra, this framework supports improved integration of wind energy into the power grid and lays a foundation for future work. Knowledge of spectral characteristics can inform estimates of the required capacity and response time of ancillary batteries and reserve power plants needed to balance the power production of wind farms. The known spectral form, when incorporated into stochastic load scheduling protocols, could help alleviate dynamic load balancing challenges. Similar spectral limits for other renewable sources, such as solar, could ultimately guide policy decisions and support the design

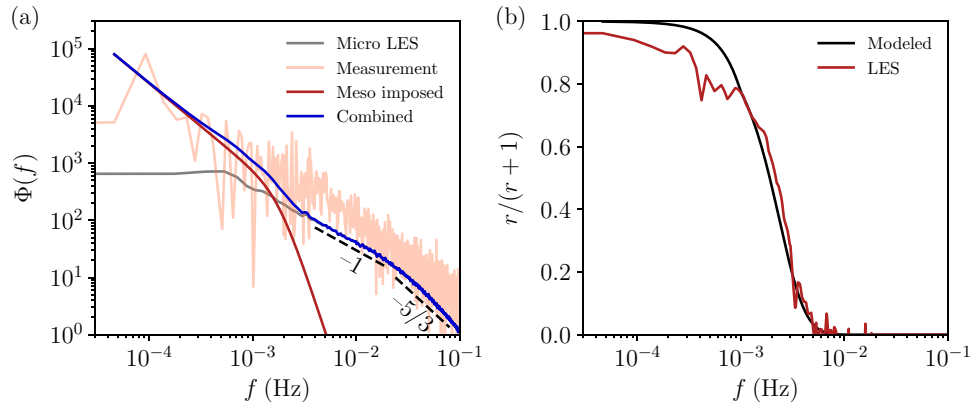


FIG. 6. (a) Atmospheric spectra reproduced in LESs, shown at a height of 87 m. “Micro LES” represents the wind spectrum measured from a standalone LES, “meso imposed” is the imposed low-frequency wind speed signal accounting for mesoscale contributions, and “combined” is the composite spectrum of “micro LES” and “meso imposed.” (b) Mesoscale contributions as a function of frequency measured from LES, along with the model results from Eq. (B1).

of an optimal energy mix for regional grids with defined resource constraints [15,37].

Future extensions of the dynamic sweeping framework could capture more realistic mesoscale-microscale interactions beyond the idealized configuration considered here. In the present study, we assume the mesoscale variability as spatially uniform and highly coherent, which is a reasonable approximation for large-scale weather-driven forcing. The same framework can be generalized to more complex settings, including spatially heterogeneous wind conditions and convective mesoscale structures. It can also be extended to account for feedback from large offshore wind farms on mesoscale flow variability. In particular, spatially varying wind conditions can be incorporated by assigning pair-specific sweeping velocities in the basis of on turbine locations and separations, since the wind-farm power spectrum is constructed from the coherence contributions of all turbine pairs [Eqs. (13) and (14)]. For convective mesoscale variability and wind-farm feedback, the introduction of a more flexible decoherence function ζ , for example, with an explicit convective form (as complex functions) and wind-farm parameters, would provide a systematic way to represent these effects and further increase model fidelity.

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DATA AVAILABILITY

The data to generate the figures in this article are openly available [38].

APPENDIX A: LARGE-EDDY SIMULATIONS OF WIND FARMS

To validate the dynamic sweeping model, we performed wind-farm LESs. The simulations were done for a neutral pressure-driven boundary layer. The numerical scheme uses pseudospectral methods in the horizontal directions, second-order finite differences in the vertical direction, and second-order Adams-Bashforth time integration. The flow domain is bounded at the top by zero vertical velocity and zero shear stress. The wall shear stress at the surface is modeled with the use of Monin-Obukhov similarity theory with roughness height $z_0 = 0.1$ m. All simulation parameters are nondimensionalized with use of the domain height H and reference friction velocity $u_*|_{t_0}$, yielding a nondimensional timescale $t_{ND} = H/u_*$. For further details, see Refs. [39,40].

To provide realistic turbulent inflow, we use concurrent precursor simulations following Stevens *et al.* [41] and Stieren *et al.* [42]. We adopt the approach proposed by Liu *et al.* [43] to model low-frequency wind speed variations in wind-farm simulations. The corresponding LES equations are as follows:

$$\begin{aligned} \partial_i \tilde{u}_i &= 0, \\ \partial_i \tilde{u}_i + \partial_j (\tilde{u}_i \tilde{u}_j) &= -\partial_i \tilde{p}^* - \partial_j \tau_{ij} - \frac{\partial_i p_\infty}{\rho} + f_i + \dot{v} \delta_{i,1}, \end{aligned} \quad (\text{A1})$$

where the tilde denotes spatial filtering at the grid scale, and $-\partial_i p_\infty / \rho$ represents the imposed driving pressure gradient, which synchronizes with the prescribed wind speed. The subgrid-scale stress tensor is defined as $\tau_{ij} = \tilde{u}_i \tilde{u}_j - \tilde{u}_i \tilde{u}_j$ and is modeled with use of the anisotropic minimum dissipation model. The filtered modified pressure is expressed as $\tilde{p}^* = \tilde{p} - p_\infty / \rho - \tau_{kk} / 3$. Turbine forces within the wind-farm domain are denoted by f_i and are modeled with an actuator disk model [44]. Viscous stresses are ignored because the Reynolds number in the atmosphere is very high. The time derivative of the imposed wind speed signal, $\dot{v} \delta_{i1}$, accounts for the forcing to drive low-frequency velocity changes, where δ_{i1} is the Kronecker δ , indicating that v acts only in the streamwise direction.

In Sec. III, the simulations were performed with a domain size of $12.56 \times 6.28 \times 1 \text{ km}^3$ on a $512 \times 256 \times 128$ grid for both the precursor and the wind-farm domain. The horizontal resolution of 24.5 m ensures that the DTU 10-MW turbine disk can be resolved with seven grid points per diameter, which is sufficient for actuator disk representation in wind-farm LESs [44,45]. For the wind farm in Sec. IV, we adopted the simulation domain size of $12.56 \times 9.42 \times 1 \text{ km}^3$ with the same spatial resolution.

APPENDIX B: MODELING ATMOSPHERIC SPECTRA

In Fig. 6(a), we show the spectrum of the imposed inflow wind speed in the wind-farm LESs. The velocity spectra demonstrate how our modeling approach allows the imposed low-frequency wind speed signal to smoothly blend with the high-frequency wind speed fluctuations that are captured by LESs. As a result, the simulation reproduces both low-frequency (mesoscale) and high-frequency (microscale) velocity fluctuations. This combination (blue line) produces a spectrum representative of atmospheric turbulence.

The low-frequency wind speed fluctuations are obtained from field measurements at the National Wind Technology Center [43,46]. On January 28, 2018, 6 h of wind speed data (4:30 a.m. to 10:30 a.m.) were collected at a height of 87 m with use of the M5 meteorological mast, which is shown in Fig. 6(a) as “measurement.” This signal was smoothed and filtered with a second-order Butterworth filter (cutoff frequency $f_c = 1.8 \times 10^{-3} \text{ Hz}$, corresponding to a timescale of about 9 min) to remove high-frequency components before being introduced into the LESs. The imposed sweeping velocity signal (details in Ref. [38]) has mean wind speed $\bar{v} = 12.14 \text{ m/s}$ and standard deviation $\sigma_v = 2.89 \text{ m/s}$ at hub height. For standalone LES, the turbulence intensity at hub height is about 12%, corresponding to a standard deviation σ_u of 1.53 m/s. Assuming the sweeping velocity and turbulence fluctuations are uncorrelated, the combined standard deviation is given

by $\sigma_{v+u} = \sqrt{\sigma_v^2 + \sigma_u^2} = 3.25 \text{ m/s}$, which is used for the random sweeping model in Eq. (3).

Both the LESs and the dynamic sweeping model use the same input spectrum. This allows a direct comparison, and highlights which spectral features are most important. Because atmospheric spectra differ by site, the framework can assess how these differences influence wind-farm power spectra by adjusting the mesoscale input of the model. As shown in Fig. 6(a), there is almost no spectral gap between the low-frequency mesoscale and high-frequency microscale ranges for the spectrum used in this study. Notably, the transitional regime in wind-farm power spectra consistently exists whether a pronounced spectral gap is visible or not. This regime arises because microscale, high-frequency turbulence is inherently less coherent than mesoscale variability, so there is always a crossover regime in-between.

In microscale wind speed spectra, there exist f^{-1} and $f^{-5/3}$ regions, which reflect the identity of wave-number spectra in turbulent boundary layers [25,47,48]. Meanwhile, field observations find that the wind power spectra follow a continuous $f^{-5/3}$ law across multiple scales [2]. Considering the mesoscale contributions to be the difference between full-scale and microscale spectra, we model the standard ratio function $r_s(f)$ as

$$r_s(f) = \begin{cases} (f_0/f_z)^{k_s+1} \times (f_0/f_H)^{-1} - 1, & f \leq f_0, \\ (f/f_z)^{k_s+1} \times (f/f_H)^{-1} - 1, & f \in (f_0, f_H], \\ (f/f_z)^{k_s+1} - 1, & f \in (f_H, f_z], \\ 0, & f > f_z, \end{cases} \quad (\text{B1})$$

where $k_s = -5/3$ is the scaling of the full-scale spectrum, f_z and f_H are the low-frequency ends of the $f^{-5/3}$ and f^{-1} regions in microscale spectra, and f_0 corresponds to the integral timescale of mesoscale processes.

We note that the wind conditions differ across sites, and a spectral gap between mesoscale and microscale regions can sometimes be observed [8,49]. This deviation from an idealized $f^{-5/3}$ spectrum can be represented with the use of a spectral gap function $\zeta_G(f) = A \exp(-Bf/f_z)$, where A controls the offset in the mesoscale region and B represents the width of the spectral gap at the mesoscale-microscale interface. Both constants can be adapted from the wind spectrum, and the corresponding mesoscale ratio function is expressed as the combination of the standard ratio function and the gap function, i.e., $r(f) = r_s(f) \zeta_G(f)$. Figure 6(b) compares the modeled mesoscale coherence $r/(r+1)$ with LES results. With the use of $f_z = 3 \times 10^{-2} \text{ Hz}$, $f_H = 10^{-3} \text{ Hz}$, $A = 0.9$, $B = 24.6$, and f_0 as the lowest imposed frequency, the parametrization reproduces the ratio of mesoscale and microscale components in the LESs.

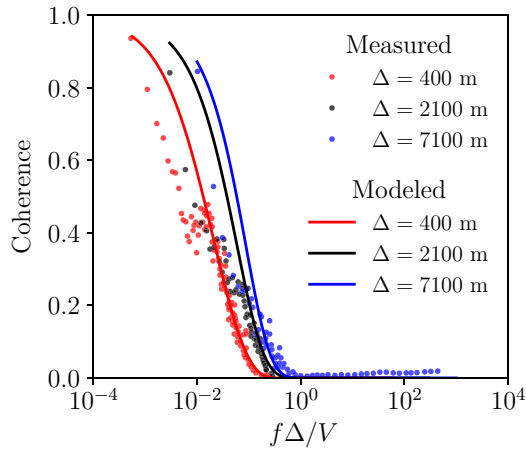


FIG. 7. Measured coherence for different turbine pairs from Mt Mercer wind farm, corresponding to Fig. 1 [20]. The solid line shows the modeled coherence given by Eq. (C1).

APPENDIX C: MODELING WIND-FARM DATA IN FIG. 1

In Fig. 7, we present coherence functions measured at the Mt Mercer wind farm, which were used to obtain the model spectrum shown here. These data underline the model predictions shown in Fig. 1. Data with different colors are collected for a range of turbine spacings, from 400 to 7100 m, with an average wind speed V of 7.1 m/s. The 400-m spacing is significantly smaller than the scale of mesoscale processes, which shows the highest wind power correlation. Interestingly, coherence in the high-frequency range ($f > 10^{-3}$ Hz) is not evident, even for the closest turbine pairs. This absence of microscale coherence is attributed to the effects of terrain and continuous wind condition changes during the measurement, which are more complex than those in well-controlled numerical environments. Nevertheless, the transition from highly coherent mesoscale structures to low coherence in the high-frequency range is consistent with our explanations. Since no mesoscale components are observed in $f \in (f_h, f_z]$, we use simplified ratio functions as

$$r_s(f) = \begin{cases} (f_0/f_H)^{k_s} - 1, & f \leq f_0, \\ (f/f_H)^{k_s} - 1, & f \in (f_0, f_H], \\ 0, & f > f_H. \end{cases} \quad (\text{C1})$$

From Fig. 1, we identified $f_z \approx 3 \times 10^{-2}$ Hz and $f_H \approx 2 \times 10^{-3}$ Hz. In the mesoscale range, the wind spectrum shows weak variability with $f^{-5/4}$ scaling; therefore, we take $k_s = -5/4$, $A = 0.12$, and $B = 1.1$.

To account for the mesoscale decoherence trend, we apply an exponential decay model ζ for Eq. (12), consistent with observations [8,17,49–51], as

$$\zeta(\omega, \Delta) = \exp\left(-a_\Delta \frac{\omega \Delta}{V}\right), \quad (\text{C2})$$

where a_Δ denotes the decay coefficient. In contrast to small-scale atmospheric turbulence, which has a strong anisotropic coherence pattern in streamwise and spanwise directions, large-scale motions decay similarly in both horizontal directions, so $a_{\Delta_x} \approx a_{\Delta_y}$. We take $a_\Delta = 1.3$ for ζ in Eq. (C2). Figure 7 confirms that the model captures the measured coherence inside the wind farm, which is then used to model the wind-farm spectra in Fig. 1.

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