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ABSTRACT
The wind power plant-wide control strategy known as wake steering involves the misalignment of upstream turbines with the wind direction to deflect wakes away from downstream turbines, increasing net wind plant power production. In this paper, we evaluate the potential of wake steering for U.S. land-based wind power plants. First, we outline a method for simulating and optimizing wake steering control for existing wind plants by combining the flow redirection and induction in steady state wake steering engineering model with the U.S. Wind Turbine Database and Wind Integration National Dataset Toolkit wind resource dataset. Next, to better understand the potential benefits of wake steering beyond those for existing wind plants, we evaluate the relative impacts of turbine specific power, turbine spacing, and mean wind speed on energy gain and levelized cost of energy (LCOE) using a model land-based wind power plant. For a subset of 60 existing wind plants, assuming a constant turbulence intensity of 8%, wake steering was found to yield an average annual energy production (AEP) gain of 0.80%, equivalent to recovering 13.85% of baseline wake losses. Further, we present a linear approximation between baseline wake losses and AEP gains that can be used to estimate wake steering gains for other wind power plants. Highlighting additional benefits of wake steering, for the model wind power plant we found that energy gains from wake steering enabled an approximate 30% reduction in turbine spacing while keeping LCOE constant.

I. INTRODUCTION
Wake steering is a plant-wide control strategy that maximizes total power production of the wind power plant by coordinating the interactions among turbines. Unlike greedy control strategies which aim to maximize the performance of individual turbines, wake steering sacrifices the power production of select turbines to achieve a higher net performance for the entire power plant. This involves the misalignment of upstream turbine nacelles with the wind direction, effectively deflecting or “steering” their wakes away from downstream turbines, yielding higher wind speeds and hence increased power production.

To model wake interactions within a wind power plant, computational fluid dynamics models are often used and validated using wind tunnel experiments and field campaigns; however, low-fidelity wake modeling tools are also necessary for evaluating the benefits of wake steering because they can be used to perform controller optimizations and estimate energy production for an entire wind power plant. One such tool set is the FLOw Redirection and Induction in Steady State (FLORIS) code developed by the National Renewable Energy Laboratory (NREL) and the Delft University of Technology. This control-orientated tool set is an open-source modular framework that models wake interactions among turbines in a wind plant and performs yaw optimizations to maximize the total power production for given atmospheric conditions, turbine specifications, wind plant layouts, and wake models.

Although the benefits of wake steering have been extensively documented, most cases are for wind tunnel experiments or for subsections of wind plants comprised of two- or six-turbine arrays evaluated at particular atmospheric conditions. To explore the potential of wake steering for large commercial wind power plants, several investigations have been conducted to optimize wind plant layouts based on existing geometries through the use of wake steering. By setting constraints on parameters such as power plant area, annual energy production (AEP) gain, and cable costs, the studies showed...
substantial potential for wake steering with increases in energy production as high as 8.5%. Finally, plant wide control has also been evaluated for a subsection of a commercial wind power plant through field tests, yielding gains as high as 14% for a downstream turbine over a 10° wind direction sector.17

In this paper, we evaluate the potential for wake steering for a set of 60 existing U.S. land-based wind power plants by running yaw optimization simulations keeping the layout constant. We assess the relative importance of different wind plant characteristics that drive the potential for wake steering, such as baseline wake losses (WL) and power density. Further, we identify trends related to different regions of the United States.

In addition to running yaw optimizations for existing wind power plants, we conduct a parametric study to investigate the relative effects of turbine spacing, wind turbine specific power (SP), and average wind speed on wake steering performance over parameter ranges relevant to land-based wind plants. This approach is similar to Fleming et al., however, this study keeps the general grid-like wind plant geometry constant. In addition to the AEP gains, for this study, the levelized cost of energy (LCOE) and balance-of-station (BOS) costs are modeled as a function of the independent wind plant parameters, illustrating the trade-offs between higher AEP and BOS costs.

The potential for wake steering is evaluated using FLORIS Version 2.1, with the Gauss-curl hybrid (GCH) wake model. Information regarding wind plant layout and turbine specifications for existing wind power plants are obtained from the publicly available U.S. Wind Turbine Database (USWTDB). Site-specific wind resource conditions are determined using numerical weather data from NREL’s Wind Integration National Dataset (WIND) Toolkit.

The remainder of this paper is organized as follows. Section II outlines the methodology used when performing yaw optimizations, highlighting the procedures for modeling wind power plants in FLORIS and obtaining wind resource information. Section III summarizes wake steering performance for the subset of existing land-based wind power plants used in this investigation, including trends related to wind plant density and region. Section IV presents results from the parametric study using the model grid wind power plant, where trends in AEP gains and BOS costs are evaluated and used to determine the impact of wake steering on LCOE. Finally, Sec. V concludes the paper, highlighting the key results and limitations of the investigation along with suggestions for future work.

II. WAKE STEERING OPTIMIZATION METHODS

The flow chart shown in Fig. 1 illustrates the key steps for evaluating wake steering potential, which are described below.

A. U.S. Wind Turbine Database

For the subset of existing wind power plants simulated, turbine coordinates as well as turbine specifications such as the rated power, rotor diameter, and hub height were obtained from the USWTDB. The USWTDB was released in 2018 and provides an overview of both land-based and offshore wind turbines in the United States. The database was jointly funded by the U.S. Department of Energy, the U.S. Geological Survey, and the American Wind Energy Association and is continuously updated by the U.S. Geological Survey, the American Wind Energy Association, and the Lawrence Berkeley National Laboratory (LBNL) with data provided by various wind power plant project developers and turbine manufacturers.

In addition to defining wind plant layouts, data from the USWTDB are used in subsequent steps for modeling wind turbines and determining the wind resource, described in Secs. II B and II D, respectively.

B. Turbine model

Wake behavior and power production computed in FLORIS are strongly dependent on the wind turbine properties. The turbine model within FLORIS is defined by tabulated power and thrust coefficients \((C_p, C_	heta)\) at an array of wind speeds as well as the rotor diameter and hub height. The combination of the two coefficients characterizes the turbine’s power performance and wake propagation behavior. The standard power equation used in FLORIS is as follows:

\[
P = \frac{1}{2} \cdot \rho \cdot A_{rotor} \cdot C_p \cdot U^3 \cdot \cos^2 \gamma,\tag{1}
\]

where \(P\) is the power produced by the turbine (W), \(C_p\) is the coefficient of power, \(\rho\) is the air density (1.225 kg/m\(^3\)), \(A_{rotor}\) is the rotor swept area (m\(^2\)), \(U\) is the wind speed (m/s), and the cosine exponent \(\gamma\) describes how fast power decreases with increasing yaw misalignment. A value of \(p = 1.88\) is used in all simulations investigated here, based on previous work fitting Eq. (1) to data from large-eddy simulations (LES) with the NREL 5-MW reference turbine. The yaw offset angle \(\gamma\) is defined as a counterclockwise rotation of the turbine nacelle from the wind direction, such that \(\gamma = \phi - \theta\), where \(\phi\) is the wind direction and \(\theta\) is the absolute yaw position relative to north.

Because the power and thrust coefficients are not readily available for each turbine in the USWTDB, a method is required to estimate them. We achieve this by scaling the \(C_p\) and \(C_	heta\) curves from the FLORIS-default NREL 5-MW reference turbine, with a rotor diameter of 126 m, hub height of 90 m, and 11.4-m/s rated wind speed.
This method assumes that the \( C_p \) and \( C_t \) curves for a given wind turbine are similar to the reference turbine when normalized to the rated wind speed.

First, we rearrange Eq. (1) to solve for the rated wind speed of the turbine of interest (\( U_{turb} \)), assuming that \( \gamma = 0 \) and the turbine’s coefficient of power at rated wind speed is equal to that of the reference turbine

\[
U_{turb} = \sqrt{\frac{2 \cdot P_{turb}}{C_{pr,ref} \cdot \rho \cdot A_{rotor,turb}}}.
\]  

where \( P_{turb} \) and \( A_{rotor,turb} \) are the rated power and rotor swept area of the given wind turbine, respectively (using data from the USWTDB), and \( C_{pr,ref} \) is the coefficient of power at the rated wind speed of 11.4 m/s for the NREL 5-MW reference turbine (0.43).

Next, \( C_p \) and \( C_t \) for the given wind turbine are modeled by scaling the wind speed axis of the corresponding curves for the NREL 5-MW reference turbine by a factor of \( U_{turb}/U_{ref} \). Figure 2 shows the \( C_p \), \( C_t \), and power curves for a turbine in the Border Winds Project wind plant (\( D = 100 \) m, \( P_r = 2 \) MW)—compared to the original curves for the NREL 5-MW reference turbine. For this example, \( U_{turb} = 9.9 \) m/s, as shown in Fig. 2(a), resulting in a shorter Region II of the power curve [Fig. 2(c)].

C. Wake model

FLORIS includes several models for calculating wake velocity deficits and wake deflection, with varying degrees of fidelity and computational cost. For example, the computationally efficient Gaussian wake model\(^{16-19}\) and relatively high-fidelity curl model\(^ {20} \) encompass both calculations.\(^ {21} \)

Although the Gaussian model has been used extensively in recent research,\(^ {10,22,23} \) it has been shown to underpredict power gains from wake steering for downstream turbines when compared to field results and LES investigations.\(^ {12} \) The importance of large-scale counter-rotating vortices in accurately predicting the power gains from wake steering was investigated by Fleming et al.;\(^ {24} \) these vortices were found to have significant effects on downstream wakes, deflecting and deforming them. Additionally, Fleming et al.\(^ {24} \) showed that these vortices permeate far downstream to turbines that are several rows deep in an array. The curl method\(^ {20} \) models these vortices and predicts the wake deflection as well as change in wake shape relatively accurately. However, the increased complexity of this model raises the computational cost (approximately 1000 times).\(^ {12} \)

With the intent to account for the effects of the counter-rotating vortices of the curl model and maintain the computational efficiency of the Gaussian model, King et al.\(^ {24} \) introduced the GCH model. The GCH model accounts for: (1) yaw-based wake recovery driven by vortices, (2) the interactions between counter-rotating vortices and the atmospheric boundary layer, and (3) secondary-steering and other multiturbine effects.\(^ {12,24} \) For a 38-turbine wind plant, simulated results using the GCH model were shown to capture more of the gains predicted by NREL’s high-fidelity Simulator for Wind Farm Applications (SOWFA) LES tool;\(^ {12} \) whereas the Gaussian model consistently underpredicts the power gains. Because this investigation focuses on large wind power plants, the GCH wake model is used here.

Additionally, models are included in FLORIS to describe wake superposition and wake-added turbulence within a wind plant.
Overlapping velocity deficits from multiple wind turbines are combined using the sum of squares method. Further, the turbulence intensity at each wind turbine location is treated as the combination of the ambient turbulence intensity and turbulence added by wakes from upstream turbines, using the model presented by Crespo and Hernández. This wake-added turbulence causes wakes to recover faster than in freestream conditions.

Finally, although efforts have been made to quantify the uncertainty in engineering wake models (e.g., the Jensen wake model), the uncertainty of the GCH model used here has not been fully assessed. As discussed, the GCH model was found to predict wake steering gains from SOWFA for a 38-turbine wind plant more accurately than the Gaussian wake model; however, depending on the specific wind direction and turbulence intensity, the relative power improvements given by the GCH model were found to differ from SOWFA results by up to 35%. A thorough uncertainty quantification of the GCH model is beyond the scope of this study. But as explained in Sec. II E, FLORIS simulations are performed at three different turbulence intensity levels to provide a reasonable range of wake losses and potential AEP gains for existing wind power plants.

D. Wind Integration National Dataset Toolkit

NREL’s WIND Toolkit includes meteorological, power production, and power forecast datasets to support grid integration research. The Weather and Research Forecasting (WRF) model was used to produce minute-resolution model output data for seven years on a uniform 2-km grid encompassing the continental United States. In this investigation, we use the publicly available 1-h resolution data for the same 7-year time period and 2-km grid spacing. The wind resource for a particular wind power plant location is characterized using wind speed and direction data from WIND Toolkit at coordinates corresponding to the average of all turbines in the wind plant at the turbine hub height.

To calculate AEP, FLORIS simulations are performed for wind directions at intervals of 5° and wind speeds ranging from 0 to 25 m/s at intervals of 1 m/s. Simulation results are then weighted by the normalized frequency of each wind direction and wind speed combination. An example wind rose illustrating the normalized frequencies of each wind direction and wind speed for the Border Winds Project wind power plant is shown in Fig. 3 for the Border Winds Project wind power plant. This wind rose indicates that the most frequent wind direction is approximately 315° with wind speeds often occurring up to 15 m/s, and wind directions near 90° occurring the least often.

E. Turbulence intensity and atmospheric stability

Atmospheric stability and ambient turbulence intensity greatly impact wake losses and the performance of wake steering. Several LES studies have shown the strong correlation between atmospheric stability and wake characteristics, mainly concerning the spatial distribution of the mean velocity deficit and the turbulence levels within the wake region. In general, higher turbulence caused by a thermodynamically unstable atmosphere leads to higher levels of flow entrainment, causing a faster rate of wake recovery. Additionally, turbulence plays a major role in wake meandering, where high turbulence intensity—typical of a stable atmosphere—leads to a narrow wake profile, causing high wake losses; and high turbulence intensity leads to a broader wake profile and lower losses. Several meteorological measurements are required to accurately represent atmospheric stability, and the question of how to include stability explicitly in engineering wake models is still an active area of research.

The FLORIS GCH wake model used here represents the state of the atmosphere using several parameters, such as turbulence intensity, wind shear, and wind veer. Turbulence intensity has the greatest impact on wake behavior, affecting the degree of wake expansion and recovery. Using turbulence values of 8%–10%, FLORIS was shown to predict average wake losses and wake steering gains from a field campaign reasonably well. Because there is large variability in the actual wake behavior at a given site due to the strong dependence on wind resource and terrain—as well as the potential dependence on the wind plant layout—wake steering simulations are performed for the 60 existing U.S. wind power plants using fixed turbulence intensity values of 6%, 8%, and 10% to quantify uncertainty in the simulation results.

F. Optimization procedure

Yaw optimizations are performed in FLORIS Version 2.1 using the sequential least squares programming (SLSQP) method within the SciPy package. Net wind plant power production is maximized by iterating through yaw offsets in the range γ = (−25°, +25°) for each wind turbine. Optimal yaw offsets are found for each wind speed and direction combination given by the wind rose. For reference, simulations are also performed for the baseline case without wake steering as well as a no-wake case. The standard FLORIS power calculation procedure used here assumes no uncertainty in the wind direction and predicts energy gains through wake steering for cases where the yaw misalignment falls on the optimized value with no uncertainty or controller lag.

G. Wake steering performance summary

Given the wind plant power results from the optimization stage, the total wind plant AEP for the no-wake, baseline, and optimized cases is calculated as follows:

![Example wind rose for the Border Winds Project wind power plant summa-](image-url)
where $AEP$ is the annual energy production; $P_i$ is the power output of the entire wind plant at a given wind speed and wind direction combination; and $t_i$ is the time in a given year spent at the respective combination, which is determined from the wind rose (see Fig. 3).

The main metric that describes the effectiveness of wake steering is the percentage $AEP$ gain compared to the baseline case. In addition, wake loss percentages ($WL$) are calculated as

$$WL = \left(1 - \frac{AEP}{AEP_{\text{no-wake}}}\right) \cdot 100,$$

where $AEP_{\text{no-wake}}$ represents the ideal energy production without wake effects. Wake losses for the optimized and baseline cases are then used to calculate the percentage reduction in wake losses from wake steering,

$$WL_{\text{red}} = \left(1 - \frac{WL_{\text{optimized}}}{WL_{\text{baseline}}}\right) \cdot 100.$$  

As an example, the wake steering performance for the Border Winds Project wind power plant is shown in Table I. For this case, the $AEP$ gain of 0.4% indicates a relatively high potential, reducing wake losses by 11.1%, corresponding to approximately 3 GWh of extra energy production per year using wake steering.

The dependence of wake steering performance on wind direction is illustrated in Fig. 4 for the Border Winds Project wind plant. Figure 4(a) shows the normalized energy distribution across the wind power plant, indicating regions where high energy production can be expected, with a peak near 325°, consistent with the wind rose (Fig. 3). The wind plant efficiency plot [Fig. 4(b)] highlights two regions with large discrepancies between the baseline and optimized wind power plant performance, near 60° and 240°. The flow fields at the two wind directions (regions I and II, respectively) are shown on the left of Fig. 4. For the wind directions in regions I and II, the turbines are relatively in-line, causing more baseline wake losses and hence lower wind plant efficiency; therefore, these regions represent cases that favor wake steering, where deflected wakes increase wind plant efficiency. As a result, we see large peaks in the percentage $AEP$ gain [Fig. 4(c)] for these two regions. Although the potential for wake steering is high for these regions, these peaks do not necessarily indicate a substantial increase in energy. In Region I, the normalized energy is less than 0.1 because this is a scarce wind direction—hence the effects of wake steering are almost lost; however, Region II has a higher normalized energy because the wind direction of 240° is more frequent, allowing wake steering control to make a significant impact.

TABLE I. Wake steering performance summary for the Border Winds Project wind power plant.

|                | No-wake | Baseline | Optimized |
|----------------|---------|----------|-----------|
| AEP (GWh)      | 706.6   | 681.1    | 683.9     |
| Wake loss (%)  | …       | 3.6      | 3.2       |
| AEP gain (%)   | …       | …        | 0.4       |
| Wake loss reduced (%) | …    | …        | 11.1      |

III. WAKE STEERING POTENTIAL FOR EXISTING U.S. LAND-BASED WIND POWER PLANTS

This section includes an overview of the locations and wind plant specifications of the subset of existing U.S. wind power plants selected from the USWTDB in Sec. III A and the respective wake steering optimization results in Sec. III B.

A. Overview of selected U.S. land-based wind power plants

The USWTDB includes approximately 1500 wind power plants. For this study, a subset of 60 wind plants was chosen to perform the wake steering optimizations. The selection of the subset was guided by the desire to represent a range of wind plant sizes [both number of turbines and capacity (MW)] for each region. The geographic locations of the wind power plants in this study are summarized in Fig. 5, where the marker color represents the region of the wind plant as defined by LBNL. For the studied subset, wind plant sizes range from six to 116 turbines, with rated turbine powers from 1.5 to 3.45 MW, and turbine specific powers (the ratio of rated power to turbine swept area) ranging from 194 to 384 W/m². The number of wind plants selected for each region reflects the respective level of wind development. For example, 20 power plants were selected for the Interior region because it contains the greatest installed capacity, as suggested by the high average wind speeds. The Southeast has historically had the lowest potential for wind development because of its relatively poor wind resource; thus, only seven wind plants were chosen for the region. Only isolated wind power plants were selected to rule out the effects of wakes from surrounding wind plants, which are not accounted for in our models.

The number of turbines, wind power plant capacity (MW), and plant power density (MW/km²) for the selected wind plants are illustrated with histograms in Fig. 6. Wind plant power density is calculated using a convex hull method while accounting for a 300 m buffer around the peripheral turbines. The range of the number of turbines and capacity is consistent across the regions, yielding a well-defined set of wind plant sizes.

B. Results for U.S. land-based wind power plants

The distribution of $AEP$ gains from wake steering is presented in Sec. III B 1. A discussion of the magnitudes of the optimal yaw offsets used for wake steering follows in Sec. III B 2.

1. Annual energy production gains

The distributions of the percentage $AEP$ gains from wake steering and the respective percentages of wake losses recovered are shown in Figs. 7(a) and 7(b), respectively, for fixed ambient turbulence intensity values of 6%, 8%, and 10%. The average percentage $AEP$ gains are 1.11%, 0.80%, and 0.61% for turbulence intensity values of 6%, 8%, and 10%, respectively. An increase in percentage $AEP$ gain is expected with decreasing turbulence intensity because wakes dissipate at a slower rate with stable, lower turbulence atmospheric conditions, resulting in more opportunities for wake steering to mitigate wake losses. As turbulence intensity decreases, the standard deviation of the percentage $AEP$ gains increases as well. Because the wind power plants all have varying turbine spacings within them, the relative effects of
Turbulence intensity on AEP gain will vary from one wind plant to another. As a result, the distribution curves show wider spreads in AEP gain as turbulence intensity decreases. The percentage of wake losses recovered shown in Fig. 7(b) is consistent with the predicted percentage AEP gains, with average wake loss recoveries of 17.05%, 13.85%, and 11.68% for 6%, 8%, and 10% turbulence intensities, respectively. But unlike Fig. 7(a), Fig. 7(b) shows an increase in wake loss recovery standard deviation as turbulence intensity increases. The
outliers between 30% and 35% wake loss recovery correspond to the outliers in percentage AEP gains, with gains up to 3.17%.

Distributions of wake losses and AEP gains from wake steering grouped by region are shown in Fig. 8 for a turbulence intensity of 8%. In general, wind power plants in the Great Lakes, Southeast, and Northeast show higher baseline wake losses than in the West and interior regions. The baseline wake losses are consistent with trends in the population density of each region, where the Northeast, Southeast, and Great Lakes regions have higher densities than the Interior and West on average. Hence, the area available for wind power plant development is likely reduced, pushing wind plant layouts to be more densely spaced. Contrarily, wind power plants in the Interior have fewer land area constraints, resulting in fewer wake losses. The percentage AEP gains shown in Fig. 8(b) are consistent with the baseline

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FIG. 6. Frequency histograms for number of turbines, wind power plant capacity (MW), and power density (MW/km²) of the wind power plants analyzed in this study for each region. The number of wind plants selected from the USWTDB in each region is listed on the upper left of each row. The number of turbines for each wind plant is found from the USWTDB, and the capacity is the sum of the rated power (MW) of all the turbines in each wind plant. Wind plant power density is the ratio of wind power plant capacity and the convex hull area.

FIG. 7. Frequency distributions of (a) percentage AEP gains and (b) percentage wake losses recovered for the set of 60 existing U.S. wind power plants with 6%, 8%, and 10% turbulence intensities, along with corresponding Gaussian kernel density estimates (solid lines). Mean, median, and standard deviation values are shown for the simulated AEP gains.

FIG. 8. Frequency histograms for number of turbines, wind power plant capacity (MW), and power density (MW/km²) of the wind power plants analyzed in this study for each region. The number of wind plants selected from the USWTDB in each region is listed on the upper left of each row. The number of turbines for each wind plant is found from the USWTDB, and the capacity is the sum of the rated power (MW) of all the turbines in each wind plant. Wind plant power density is the ratio of wind power plant capacity and the convex hull area.
wake losses in each region. Outliers in the Great Lakes, Southeast, and Northeast highlight the fact that wake steering potential depends on more than the baseline wake losses experienced. These outlier wind plants contain long rows of closely spaced turbines (e.g., along ridges). Although the wind directions corresponding to the long rows may not be the most frequent, their occurrence leads to substantial wake loss reduction from wake steering because of secondary steering effects. Overall, Fig. 8(b) suggests that existing wind power plants in the Great Lakes, Southeast, and Northeast regions tend to have the highest potential for wake steering, likely because of the presence of more land development constraints.

Figure 9 shows the relationships between percentage AEP gain, percentage baseline wake losses, and wind plant power density for a turbulence intensity value of 8%, along with equations for the corresponding linear regressions and respective $R^2$ values. Figure 9(a) shows a general increase in percentage AEP gain with increasing percentage baseline wake losses, with the following linear fit:

$$\% \text{AEP}_{\text{Gain}} = 0.18 \cdot WL_{\text{baseline}} - 0.15.$$  (6)

Although several outliers are apparent because of the sensitivity of wake steering performance to wind resource, wind plant layout, and total wake losses, this relationship can be used to predict a “ballpark” figure for percentage AEP gain given the baseline wake losses.

Similarly, Fig. 9(b) suggests a general increase in percentage AEP gain with increasing wind plant power density (MW/km²), consistent with the trends in Fig. 8.

Whereas the baseline wake losses shown in Fig. 9(a) are mostly between 2% and 8%, with a mean value of 5.33%, resulting in an average AEP gain of 0.8%, wake losses reported in other sources suggest an even higher potential for wake steering. A summary of estimated and observed wake losses reported in the literature presented by Lee and Fields shows wake losses ranging from roughly 5% to 20% for a variety of projects. For this range of wake losses, the linear relationship found in Fig. 9(a) predicts expected AEP gains from wake steering ranging from 0.75% to 3.5%.

2. Optimal yaw offsets

To reveal the degree of yaw misalignment required to achieve the AEP gains presented, Figs. 10(a) and 10(b) show the percentage of time turbines spend with yaw misalignments larger than $1^\circ$ in magnitude and the distributions of the nonzero yaw offsets among all wind power plants and turbines, respectively. Figure 10(a) shows that turbines experience yaw misalignments higher than $1^\circ$ relatively often for all turbulence intensity values. The mean percentage of time spent operating misaligned with the wind increases slightly with decreasing turbulence intensity, from 29.6% to 36.3% of the time for the 10% and 6% turbulence intensities, respectively; however, the general shapes of
the curves remain consistent, with the standard deviation changing only slightly from 11.5% to 13.1% for the 10% and 6% turbulence intensities, respectively. Despite these large fractions of time spent yawing, Fig. 10(b) suggests that when operating with a yaw offset, turbines spend most of the time experiencing small yaw misalignments; optimal yaw offset magnitudes between $0 \sqrt{C_{14}}$ and $5 \sqrt{C_{14}}$ occur 82%, 86%, and 89% of the time for the 6%, 8%, and 10% turbulence intensity cases, respectively, including times when no offsets are applied.

Finally, Figs. 11(a) and 11(b) show the relationships between the average yaw misalignment in the wind power plant and the percentage baseline wake losses and percentage AEP gain, respectively. Figure 11(a) suggests a strong correlation, where higher baseline wake losses create opportunities for more turbines to operate with larger offsets. Last, the trend shown in Fig. 11(b) between the percentage AEP gain and the average yaw offset is slightly weaker, with an $R^2$ value of 0.54; therefore, large optimal yaw misalignment magnitudes resulting from high baseline wake losses are not the sole predictor of good wake steering performance.

**IV. PARAMETRIC WAKE STEERING STUDY**

The analysis in Sec. III revealed general trends, such as the dependence of AEP gains from wake steering on baseline wake losses and wind plant power density. However, because each wind power plant has varying characteristics—such as turbine spacing and wind resource—it is difficult to isolate the impacts of certain parameters on wake steering performance. Hence, the objective of this parametric study is to evaluate the relative impacts of individual wind power plant and turbine specifications on wake steering performance for a model land-based wind plant. In addition, effects on the LCOE are evaluated while considering the trade-offs between BOS costs and AEP for baseline and optimized cases. Sections IV A and IV B provide an overview of the methods and results for the study, respectively.

**A. Parametric study method**

The constant and independent variables used in the parametric study are summarized in Table II. A $7 \times 7$ square grid layout is used, with each of the turbines having identical specifications. Turbine scaling to vary the specific power is performed by adjusting the rated power using the method described in Sec. II B. Simulations are performed for all combinations of the independent variables, using a constant turbulence intensity of 8%.

To estimate the impact of wind plant parameters on BOS costs, the NREL LandBOSSE model is used. The model follows both...
process-based trends (e.g., site preparation, electrical collection, foundation construction, and turbine installation) and empirical curve fits. In this analysis, the management, collection, road, and erection costs vary because of the change in turbine physical spacing, turbine rating, and total project capacity, whereas the number of turbines in each scenario is constant. For example, as turbine relative spacing decreases, the total length of roads, collection cables, trenches, and time to walk cranes between turbines decreases, which results in reduced costs for these scopes of work. Management costs also decrease as the total costs of these other areas decrease. The relationship between LCOE and BOS costs is summarized in the following equation:37

\[ LCOE = \frac{FCR \ast (BOS + TCC) + OpEx}{AEP}, \]  

where LCOE is the levelized cost of energy, FCR is the fixed charge rate (%) per year, BOS and TCC are the balance-of-station and turbine capital costs, respectively, and OpEx represents the operational expenditures per year. As a function of installed capacity, we assume constant TCC and OpEx values of 1011 $/kW and 44 $/kW/yr, respectively, and an FCR of 7.5%/yr.37

The location of the model wind plant—used to determine the wind rose from WIND Toolkit data—is shown in Fig. 5 by a yellow star at a latitude and longitude of 40.995° and −84.566°, respectively. A representative location in Ohio was chosen because the wind resource results in a wide range of directions that produce significant contributions to energy production, as shown in Fig. 12. Because it is difficult to avoid significant wake interactions for a site with a more uniform distribution, the resulting wake losses are relatively high; therefore, the site lends itself well to wake steering. The average wind speed for the location is 6.95 m/s, and the predominant wind direction is from the southwest. Because mean wind speed is treated as an independent variable, a scaling factor is applied to achieve a desired average. The regular grid wind power plant layout is assumed because the actual layouts of wind plants in this location are driven by siting wind turbines around existing homes and infrastructure.

### B. Results for the parametric study

Using the parametric study method outlined in Sec. IV A, Secs. IV B.1 and IV B.2 summarize the impacts of wind power plant characteristics on wake steering performance with respect to AEP gains and LCOE, respectively.

#### 1. Annual energy production gains

Figure 13 shows the percentage baseline wake losses and respective percentage AEP gains for the model wind power plant using a variety of relative turbine spacings between 4D and 15D; average wind speeds of 6.0, 7.5, and 9.0 m/s; and turbine specific powers of 150, 200, 250, and 300 W/m². The variation of baseline wake losses with turbine spacing is consistent with expectations; as the relative spacing increases, the wakes have more time to dissipate before reaching downstream turbines, reducing the percentage baseline wake losses. As turbine spacing increases, the curves asymptotically approach zero baseline wake losses across all wind speeds and turbine-specific powers. Further, the shapes of the respective percentage AEP gain curves for each average wind speed are also consistent with the baseline wake losses, where higher wake losses lead to more potential for wake steering and hence higher AEP gains.

At each average wind speed, an increase in wind turbine-specific power leads to systematically higher baseline wake losses. A higher turbine-specific power indicates a higher rated wind speed and hence larger Region II of the power curve [Fig. 2(c)]; therefore, because of the high thrust coefficients in Region II, higher specific powers result in more baseline wake losses. The AEP gain curves for different specific powers reflect their respective wake loss curves, where higher baseline wake losses lead to more gain.

Finally, increasing the mean wind speed systematically reduces the baseline wake loss curves. Although the turbine spacings where the wake losses for each specific power begin to converge remain relatively constant (near 10D), the magnitudes of the maximum baseline wake losses reduce from between 17% and 23% at 6.0 m/s to between 7% and 13% at 9.0 m/s, depending on turbine specific power. As the average wind speed increases, turbines spend a larger fraction of time operating above rated wind speed, where rotor thrust decreases [Fig. 2(b)], leading to lower wake losses. The respective percentage AEP gain curves for each wind speed [Figs. 13(d)–13(f)] reflect this behavior as well, where the lower baseline wake losses lead to less potential for wake steering and hence lower AEP gains.
2. Impacts on levelized cost of energy

As a function of installed capacity, the dependence of the BOS costs on relative turbine spacing and turbine-specific power is shown in Fig. 14. BOS costs decrease significantly with increasing turbine-specific power because of the reduced site preparation, development, and management costs per unit of installed capacity. Although relatively minimal, increasing turbine spacing leads to higher BOS costs.
suggesting a trade-off between BOS costs and the baseline AEP shown in Fig. 13, and hence a possible inflection point in LCOE as a function of turbine spacing.

The sensitivity of LCOE to wake steering and BOS costs is illustrated in Fig. 15 at different turbine spacings for a wind turbine specific power of 150 W/m² and average wind speed of 9.0 m/s. Curves for LCOE with constant BOS costs—equal to those at 15D turbine spacing—and variable BOS costs are compared for the baseline and optimized cases relative to the LCOE at 15D turbine spacing. For both the constant and variable BOS cost scenarios, the optimized curves have lower LCOE because of the higher AEP at each spacing; however, as the spacing increases, the baseline and optimized curves converge near 10D spacing because there are lower baseline wake losses and hence less AEP gain for the optimized cases. Clear inflection points are visible in the LCOE curves with variable BOS costs (at 7D turbine spacing for the optimized case and 10D spacing for the baseline case). These points represent the relative spacings at which the benefits of higher AEP no longer outweigh the increased BOS costs related to larger turbine separations. The benefits of wake steering are evident from the shift of the inflection point to a lower relative spacing, indicating that an optimum LCOE can be achieved with a denser wind plant layout when employing wake steering.

Although the inflection points in Fig. 15 reveal how wake steering can influence the optimal wind power plant layout, the combination of a low wind turbine specific power and high average wind speed is uncommon in typical wind plants. Hence, Fig. 16 illustrates the baseline and optimized LCOE curves for different average wind speeds at the two specific power extremes investigated here. Across the two wind turbine specific powers, an increase in average wind speed leads to a decrease in LCOE for both the optimized and baseline cases. Because higher average wind speeds correspond to a decrease in baseline wake losses and an increase in AEP with fixed BOS costs, the decrease in LCOE is consistent with trends shown in Fig. 13.

Although inflection points where LCOE is minimized at a particular turbine spacing do not exist for a wind turbine specific power of 300 W/m², Figs. 16(a)–16(c) show the increasing presence of inflection points as mean wind speed increases for the 150 W/m² specific power case. As the average wind speed increases, wake losses become smaller (see Fig. 13), creating a more prominent trade-off between AEP and BOS costs at higher turbine spacings. An inflection point is visible at an average wind speed of 7.5 m/s in Fig. 16(b); however, the inflection point for both the baseline and optimized cases occurs near the same turbine spacing of 10D. But as the average wind speed increases to 9.0 m/s, the turbine spacing with minimum LCOE shifts to 7D for the optimized case because of the further reduction in wake losses. For each average wind speed, the corresponding LCOE curves for a wind turbine specific power of 300 W/m² are shown in Figs. 16(d)–16(f). With higher specific-power turbines, wind power plants experience more significant AEP gains as turbine spacing increases because of more prominent overall wake losses. Hence, the high-specific-power scenarios do not exhibit an inflection point for the range of turbine spacings investigated because the additional AEP always outweighs the increase in BOS costs for larger turbine spacings.

LCOE improvements from wake steering as well as the ability of wake steering to enable higher wind plant power densities can be visualized in Fig. 17, which shows the relationship between LCOE and wind plant power density for different turbine specific powers at an average wind speed of 7.5 m/s. Note that an inflection point in LCOE is evident for the 150 W/m² case just below a power density of 2 MW/km², consistent with Fig. 16. Further, Fig. 17 shows that as the wind turbine specific power increases, the relative benefits of using wake

FIG. 14. BOS costs ($/kW) as a function of relative turbine spacing at wind turbine specific powers of 150, 200, 250, and 300 W/m², shown in purple, green, crimson, and yellow, respectively.

FIG. 15. Percentage change in LCOE relative to the baseline LCOE with 15D turbine spacing for a wind turbine specific power of 150 W/m² and average wind speed of 9.0 m/s. Green curves show the change in LCOE assuming constant BOS costs equal to the costs at 15D spacing, and purple curves show LCOE with the change in BOS considered. Solid and dashed curves represent baseline and optimized cases, respectively.
steering decrease; for an example wind plant power density of 4 MW/km², an LCOE reduction of —1.2% occurs between the baseline and optimized cases at 150 W/m² yet there is a reduction of only —0.66% at 300 W/m².

Finally, Fig. 17 illustrates how the AEP gains from wake steering allow higher wind plant power densities to be achieved for a specific LCOE. For example, for a target LCOE of 38 $/MWh, using turbines with a specific power of 200 W/m², wake steering enables an increase
in power density from 4.4 to 7.4 MW/km², representing an improvement of 68%.

V. CONCLUSIONS

In this paper, we introduced a methodology for estimating AEP gains from wake steering using the FLORIS engineering wind plant control tool, USWTDB, and the WIND Toolkit dataset. Wake steering simulations were run for a set of 60 existing U.S. wind power plants as well as for a parametric study investigating the impact of wind plant parameters on wake steering performance using a generic land-based wind plant model. Further, simulation results were analyzed using NREL’s BOS and LCOE cost models to evaluate the trade-offs between AEP and BOS costs for both baseline and optimized scenarios and to better understand the relative impacts of wind plant parameters on the LCOE.

The wake steering simulations for the set of 60 existing wind power plants revealed average AEP gains of 1.11%, 0.80%, and 0.61% for turbulence intensities of 6%, 8%, and 10%, respectively. Many factors determine the potential AEP gain from wake steering, but a simple linear regression model relating baseline wake losses to AEP gain was developed for a turbulence intensity of 8%, revealing greater opportunities for wake steering as wake losses increase. For example, although average wake losses are only 5.33% for the 60 existing wind plants investigated, for projects with baseline wake losses between 6% and 12%, AEP gains of 1%–2% are predicted. Thus, as siting constraints become more restrictive—causing wake losses to increase—the potential for wake steering will also increase.

The simulations for the 60 existing wind power plants also revealed a high sensitivity of the AEP gains to the ambient turbulence intensity. Hence, future research should focus on improving predictions of site-specific turbulence intensity characteristics within engineering wake models. For example, several studies have used site-specific meteorological data to model turbulence intensity as a function of stability parameters such as Monin–Obukhov length and wind speed, both of which are available in WIND Toolkit.

Although turbines were found to operate with optimal yaw misalignments greater than 1° approximately 30% of the time, the magnitudes are relatively low, with offsets from 0° to 5° occurring between 80% and 90% of the time, depending on turbulence intensity. Nevertheless, these high fractions of time spent yawing might be of concern to wind power plant owner/operators. Hence, future research could explore how much of the potential AEP gain can be captured when constraining the amount of time turbines can spend misaligned with the wind. Alternatively, a limit on the number of turbines that can be yawed could be imposed, introducing another optimization problem to identify which turbines in the wind plant have the largest impact on AEP performance when yawed.

The wake steering simulations in this investigation were performed assuming no wind direction uncertainty; however, wake steering controllers must perform in dynamic wind conditions where turbines’ yaw positions will not track the upcoming wind direction perfectly. Several authors have investigated the impact of wind direction variability on wake steering performance, showing that although energy gains are reduced, robust wake steering controllers can be designed to help mitigate the effects of wind direction uncertainty. Simley et al. showed that wake steering simulations including wind direction uncertainty tend to match results from a field experiment at a commercial wind plant. FLORIS includes a method for incorporating the effects of wind direction uncertainty, but due to the drastic increase in computational expense the method was not applied to the wind plants in this investigation. However, future research could evaluate the effects of realistic wind direction uncertainty for a subset of the simulation cases presented here.

For the parametric study, wind plants with low turbine spacing, low average wind speed, and high turbine specific power yielded the highest wake steering performance. This is consistent with results for the 60 existing wind power plants, where more wake steering potential was observed for wind plants with higher power densities. For all wind plant configurations, the AEP gains from wake steering translate directly to a reduction in LCOE; however, incorporating simulation results with the LCOE model, including BOS costs, showed that, in general, LCOE can also be reduced by simply increasing the turbine spacing because the associated higher AEP tends to outweigh the additional BOS costs for both the baseline and optimized cases. But for scenarios with low turbine specific power and high average wind speed, an inflection point was observed, where the trade-off between AEP and BOS costs results in a particular turbine spacing (near 10D) that minimizes LCOE. For the extreme case with a specific power of 150 W/m² and an average wind speed of 9 m/s, the inflection point shifts to 7D when accounting for the AEP gains from wake steering.

Finally, wake steering for more typical average wind speeds and wind turbine specific powers was found to permit a significant increase in wind plant power density while maintaining a specific LCOE. For example, with a target LCOE of 38 $/MWh, wake steering enabled a 68% increase in power density.

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DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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