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Validation of FAST.Farm Against Full-Scale Turbine SCADA Data for a Small Wind Farm

K. Shaler[1], M. Debnath[1], and J. Jonkman[1]

[1]National Renewable Energy Laboratory, Golden, CO 80401, USA

E-mail: `kelsey.shaler@nrel.gov`

Abstract. FAST.Farm is a new midfidelity engineering tool developed by the National Renewable Energy Laboratory targeted at accurately and efficiently predicting wind turbine power production and structural loading in wind farm settings, including wake interactions between turbines. FAST.Farm is based on some of the principles of the Dynamic Wake Meandering model—including passive tracer modeling of wake meandering—but addresses many of the limitations of previous Dynamic Wake Meandering (DWM) implementations. Previous FAST.Farm verification studies show the similarities and differences between FAST.Farm and large-eddy simulations for rigid and flexible turbines. In this validation study, FAST.Farm turbine responses are compared to multiturbine measurements from a subset of a full-scale wind farm. FAST.Farm predictions of turbine generator power, rotor speed, and blade pitch for five-turbine simulations are compared to supervisory control and data acquisition results. Results reveal that FAST.Farm generator power mean and standard deviation results reasonably match measured data for upstream and downstream turbines, as well as the mean rotor speed and blade pitch above rated wind speeds. However, FAST.Farm generally underpredicts the mean rotor speed and overpredicts the mean blade pitch below rated operation. These errors are likely related to inaccuracies in the generic controller simulated. Despite controller differences, FAST.Farm predicts the same overall relative rotor power trends for all waked turbines at all wind speeds.

1. Introduction

In the context of wind farm design and optimization, it is crucial to be able to perform thousands of wind-farm-scale simulations expediently. FAST.Farm is a midfidelity tool developed by the National Renewable Energy Laboratory (NREL) for this purpose. FAST.Farm models the wind turbine dynamics and wake physics of wind farms for the purpose of accurately and efficiently predicting wind turbine power production and structural loading. This includes wake interactions between turbines based on advancements to the Dynamic Wake Meandering (DWM) model [5]. In past work, FAST.Farm was verified against results from the large-eddy simulation (LES) model known as the Simulator fOr Wind Farm Applications (SOWFA). Results were compared for laterally aligned three-turbine configurations with different inflow and control conditions using turbulent ambient wind data generated by a LES precursor and synthetic inflow [6, 9]. From these studies, FAST.Farm mean turbine power and thrust differed from SOWFA results by an average of $< 5\%$ for both rigid and flexible turbines, while the standard deviation varied by an average of < 25%. Overall, higher differences were seen for cases with lower ambient turbulence intensity (TI) and yawed turbines due the lack of wake-added turbulence and curled wake in FAST.Farm. Additionally, horizontal and vertical wake meandering, as well as wake-deficit advection, evolution, and merging, were captured reasonably well by FAST.Farm. FAST.Farm-predicted structural response has also been shown to compare well with coupled SOWFA-OpenFAST results for a series of small wind-farm scenarios [8]. For the 15 structural quantities of interest, most mean and standard deviation percent differences averaged below 5% and 20%, respectively. FAST.Farm has also been used to study the effects of atmospheric lateral coherence and wake meandering on downstream turbine performance [9] and fatigue loads [12, 11]. These studies found that wake meandering has a large effect on downstream turbine power production and fatigue loads, making this an important physical feature to accurately model. The only other validation study to compare FAST.Farm simulations to measurements was the Scaled Wind Farm Technology (SWiFT) benchmark study [2]. Results showed that underperforming aspects of the simulated wakes were primarily a result of inaccuracies in the inflow and not related to wake modeling itself.

The objective of this work is to assess the ability of FAST.Farm to accurately predict turbine operation in a small wind farm. This is done by comparing FAST.Farm turbine response to multiturbine measurements from a small full-scale wind farm to further validate FAST.Farm. To achieve this, FAST.Farm simulations are performed for a range of inflow conditions and compared to SCADA data from five GE 1.5-MW turbines, as shown in Figure 1. The data are collected from the turbines located at the northwest corner of a larger wind farm. Statistical results (mean and standard deviation) are compared for generator power, rotor speed, and blade pitch for the five turbines. To measure the wind inflow conditions, a 60-m meteorological mast and a WindCube-V2 profiling Doppler lidar are available just upstream of turbine Tr02 along the predominant wind direction. An ultrasonic anemometer on the meteorological mast provides 20-Hz u-, v-, and w-velocity components and wind direction time series data from a height of 50 m. The profiling Doppler lidar provides 1-Hz wind speed and wind direction data from 40 m to 260 m heights with an interval of 20 m.

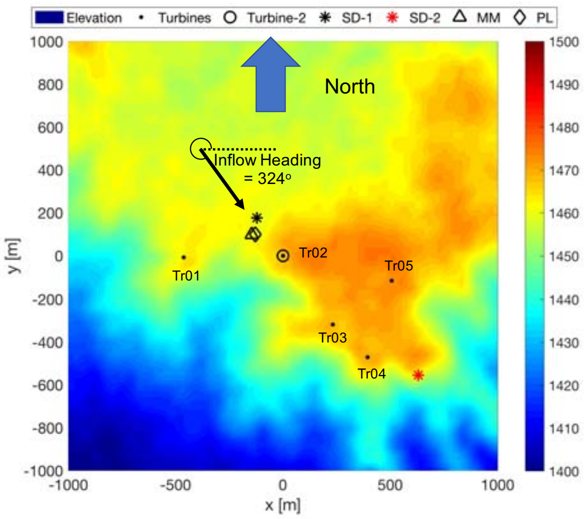


Figure 1. Wind farm layout. Tr01—Tr05 indicate the turbine locations. Contours show elevation above sea level in meters. x- and y-axis are easting and northing coordinates, respectively, centered at Tr02. The profiling Doppler lidar (PL) and meteorological mast (MM) are indicated by the diamond and triangle symbols. Sodar (SD) locations are indicated by stars but not used in this work.

2. Approach and Methodology

This section provides an overview of FAST.Farm, followed by descriptions of the validation cases that were used in this study.

2.1. Overview of FAST.Farm

FAST.Farm is a multiphysics engineering tool that accounts for wake interaction effects on turbine performance and structural loading within wind farms. FAST.Farm is an extension of the NREL software OpenFAST, which solves the aero-hydro-servo-elasto dynamics of individual turbines. FAST.Farm extends this analysis to include wake deficits, advection, deflection, meandering, and merging for wind farms.

FAST.Farm is based on the DWM model, [7] but expands on it to address many limitations of past DWM implementations. Using this method, the wake deficit of each turbine is computed using the steady-state thin shear layer approximation of the Navier-Stokes equations and the wake is perturbed with a turbulent freestream to capture wake meandering. Wake merging is modeled using a superposition method. As in OpenFAST, rotor aerodynamics are modelled using the blade-element-momentum (BEM) theory with options for advanced corrections, including unsteady aerodynamics.

2.2. Validation Cases

For this study, generator power, rotor speed, and blade pitch from the supervisory control and data acquisition (SCADA) data of all five turbines are compared for inflow cases with freestream wind speeds ranging from 6.2 to 18.7 m/s and TI values ranging from 1.4 to 14.9, as depicted in Figure 2. Wind speed range are chosen to represent a wide range of utility-scale turbine operating conditions. Inflow heading is constrained to remain within 325° ± 5° with shear exponents of 0.12 to 0.2. The profiling lidar was used to provide the inflow shear exponent based on changes to the wind speed between heights of 40 and 120 m, as well as average wind speed and wind direction collected at a height of 80 m. Wind directions were primarily selected to ensure turbine-wake interaction for Tr03 and Tr04, as well as a relatively smooth upstream topography for the inflow wind. Because of the significant amount of data, this results in 42 10-minute data sets to compare within these constraints.

For the corresponding FAST.Farm simulations, ambient wind inflow is generated synthetically by TurbSim [4], which creates two-dimensional (2D) turbulent flow fields. Turbulence is simulated using the Kaimal spectrum with exponential coherence model based on time-series point measurements of u-, v-, and w-velocity components from the sonic anemometers on the meteorological mast at a height of 50 m. That is, TurbSim uses the wind velocity measurements at this specific point to derive the wind velocity at other points across a transverse 2D grid based on the spectra of the prescribed time series and standard exponential coherence functions. By this method, the wind data match the prescribed time series at the measurement point. At other points, the wind data are spatially coherent to the prescribed time series at the measurement point, such that the wind data are more coherent at lower frequencies and the closer a point is to the measurement point. The time-dependent 2D wind field is propagated along the wind direction at the mean wind speed of the midpoint of the field. The use of this capability not only enables a statistical comparison of the numerical simulation to the data measurements, but also a direct time series comparison. Each case from the measurements is simulated in TurbSim and FAST.Farm six times, using six different random turbulence seeds to generate the wind data at the spatially coherent points (the turbulence seeds dictate the phases of the various frequency components). This was done to capture variability in the numerical simulation results associated with the uncertainty imposed by the unmeasured

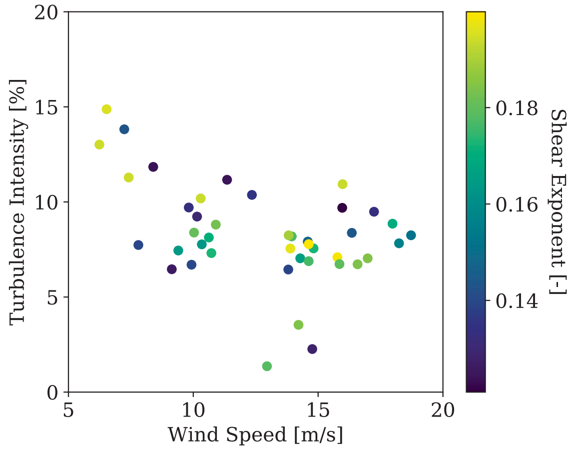


Figure 2. Turbulence intensity versus freestream velocity 10-minute average inflow conditions from sonic anemometer measurements. Each dot represents an experimental data point that is simulated by and compared to FAST.Farm.

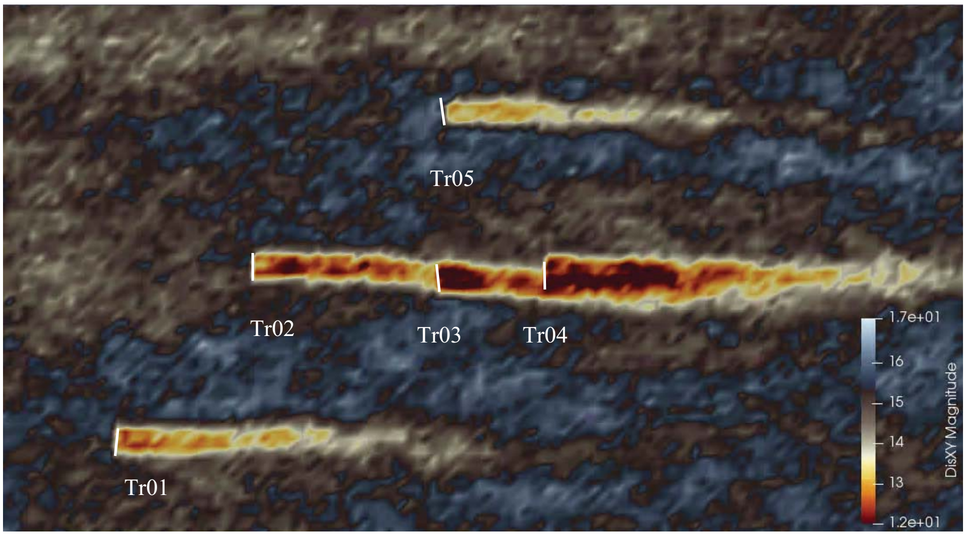
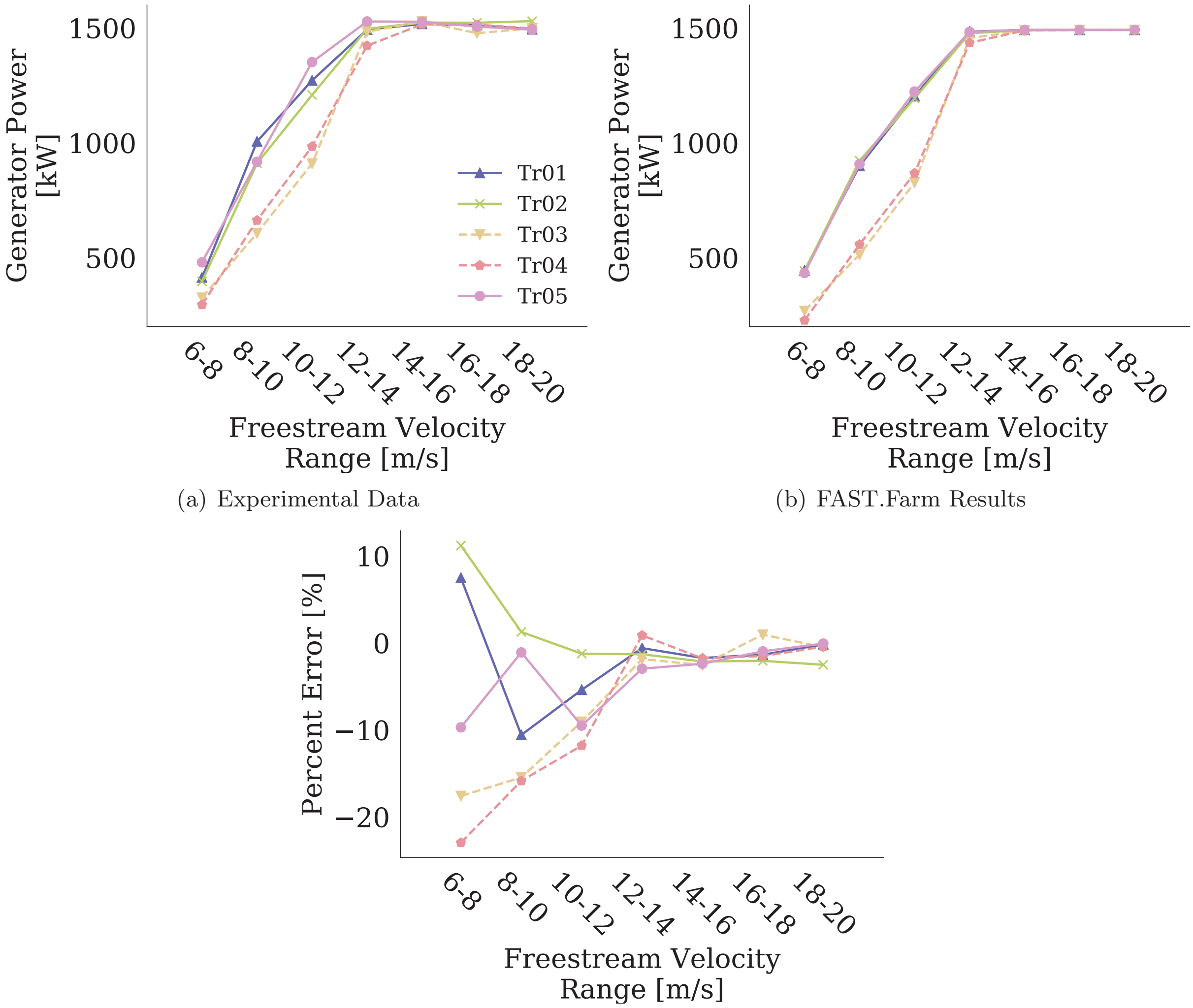


Figure 3. Instantaneous 2D flow visualization of a five-turbine FAST.Farm simulation in turbulent 6.5 m/s inflow, sampled at hub height and colored by velocity magnitude.

wind inflow.

The GE 1.5-MW turbine was used for all results. This turbine has a hub height of 80 m and rotor radius of 38.5 m and a controller supporting variable speed below rated and collective blade pitch to feather regulation above rated. In the OpenFAST model, aerodynamic, structural, and controller components were enabled. Because of the proprietary nature of the turbine controller, a generic controller was developed and used in the OpenFAST model. This model was developed at NREL using actual GE 1.5-MW turbine specifications provided by the manufacturer. [1] Though the turbine controller was originally developed as a constant-power controller, it was discovered during the course of this work that, at this site, controller logic differs between turbines and from the original logic provided by the manufacturer. In particular, most turbines appear to use constant-torque controllers, though Tr02 behaves differently for some data points. To accommodate this, the controller logic for all turbines was changed to be constant torque, with the Tr02 controller logic set to be constant power when implied by the experimental results.

For each FAST.Farm simulation case, each turbine was set to a fixed yaw misalignment angle, unique to each turbine. Direct yaw misalignment measurements are available for Tr02 and Tr04 based on lidar and nacelle yaw position measurements. For the remaining turbines, approximate yaw misalignment angles were computed by subtracting the inflow wind direction from the nacelle vane yaw position. For more details on these measurements and corresponding uncertainty, see Fleming et al. [3] The mean yaw misalignment ranges from $-20.0°$ to $16°$ for all turbines across all cases. FAST.Farm simulations were performed with a high-resolution spatial discretization of 7 m, which is fine enough to resolve the turbine response considered in this paper. A high-resolution temporal discretization of 0.05 seconds was used to match the experimental velocity data collected from the meteorological mast. Low-resolution spatial and temporal discretization vary between cases based on average hub-height inflow velocity, following the guidance derived from Shaler et al. [10] An instantaneous 2D flow visualization at hub height of the FAST.Farm simulation of the five turbines with turbulent 6.5 m/s hub-height wind speed at a inflow heading of $321.0°$, TI of 7.9%, and shear exponent of 0.17 is shown in Figure 3.



(a) Experimental Data

(b) FAST.Farm Results

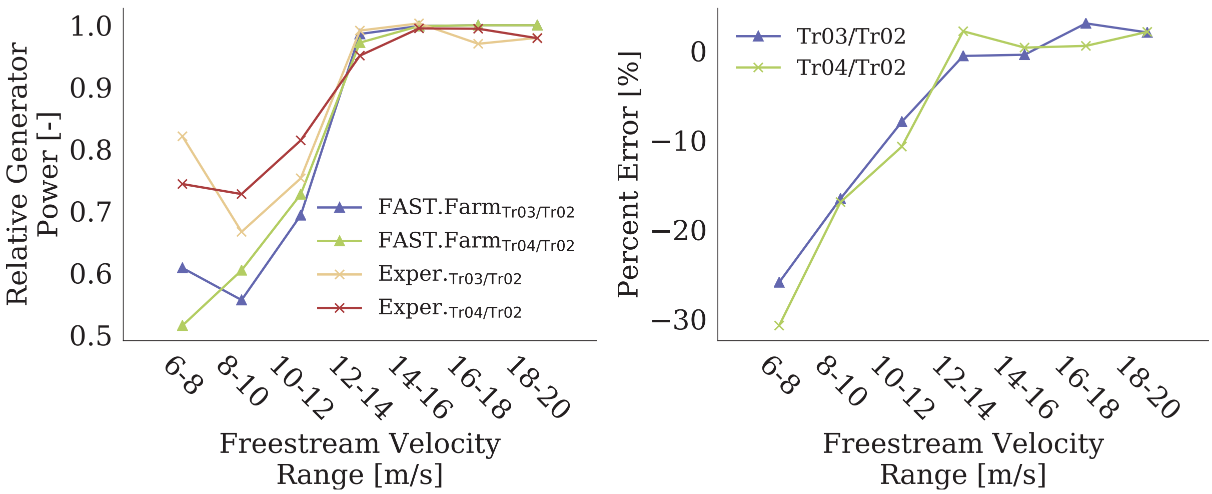
(c) Relative Power

Figure 4. Bin-averaged generator power curves for each turbine. Curves are shown for (a) experimental data, (b) FAST.Farm results, and (c) percent error between FAST.Farm results and experimental data.

3. Results

This section focuses on comparing the differences and similarities between FAST.Farm and the experimental results. Turbine responses are quantitatively assessed by comparing statistical results of generator power, rotor speed, and blade pitch for the cases shown in Figure 2.

Time-averaged power curves of each turbine are shown in Figure 4 for experimental data and FAST.Farm results across all cases and inflow velocities binned in 2-m/s intervals. As expected, experimental data and FAST.Farm results both show that waked turbines exhibit reduced generator power at below-rated wind speeds. More variation in the power curves is seen in experimental unwaked turbine response compared to FAST.Farm results. This is likely due to further variation of inflow conditions that is not captured by the inflow measurements used to construct the computational inflow. At below-rated wind speeds, FAST.Farm unwaked and waked turbine results have an average percent error of 4.5% and 15.5%, respectively. For all wind speeds, unwaked and waked turbine results have an average percent error of 2.0% and 7.1%,



(a) Relative Power (b) Percent Error

Figure 5. Bin-averaged relative generator power curves for each turbine. Computed by dividing average waked turbine power output by averaged Tr02 turbine power output. Curves are shown for (a) relative generator power of FAST.Farm and experimental data and (b) percent error between results.

respectively. The higher percent error in waked turbines is likely due to differences between FAST.Farm and experimental data in wake development and meandering of upstream turbines.

Relative power curves are shown in Figure 5 and computed by dividing average waked turbine power output by average Tr02 turbine power output, e.g., $P_{\text{rel}} = P_{\text{Tr03}}/P_{\text{Tr02}}$. There are differences between experimental and FAST.Farm relative power values for below-rated wind speed bins. In particular, FAST.Farm predicts stronger wake impact on the downstream turbines than the data at the lowest wind speeds. However, correct relative rotor power trends down the row of three turbines are accurately captured by FAST.Farm, with average percent errors of 6.6% and 7.6% for Tr03 and Tr04, respectively. In particular, relative rotor power increases with increasing inflow velocity and, with the exception of the lowest bin velocity, Tr04 produces more relative power than Tr03. FAST.Farm results have an average percent error of 18.1% and 7.1% for both turbines at below-rated and all wind speeds, respectively. The higher percent error at below-rated wind speeds is likely because wake development and meandering differs because of inconsistencies between the measured and experimental inflows. This is supported by the results in Doubrawa et al. [2].

Measured time-averaged generator power, rotor speed, and blade pitch for each wind turbine and each case are shown in Figure 6. FAST.Farm results are shown here by the filled areas that encompass the full range of mean values across all cases and seeds, binned in 2-m/s intervals. Though not shown, it should be noted that most of the variation in mean FAST.Farm results is caused by the variation across simulation cases, not by varying the turbulence seed. The below and above rated operation of the wind turbines are clearly visible, with the transition at a rated wind speed of around 12 m/s. FAST.Farm generally underpredicts the mean rotor speed and overpredicts the mean blade pitch below rated, which suggests that the generic turbine controller used in the OpenFAST model is not entirely representative of the controller implemented on the real GE 1.5-MW turbines. Regardless, the mean generator power across all wind speeds and blade pitch above rated generally match well between FAST.Farm and the measured data, with only a few cases where the measured data fall outside the range of the FAST.Farm results. The closest comparison is for turbine Tr02 because the wind inflow was measured just upwind of this

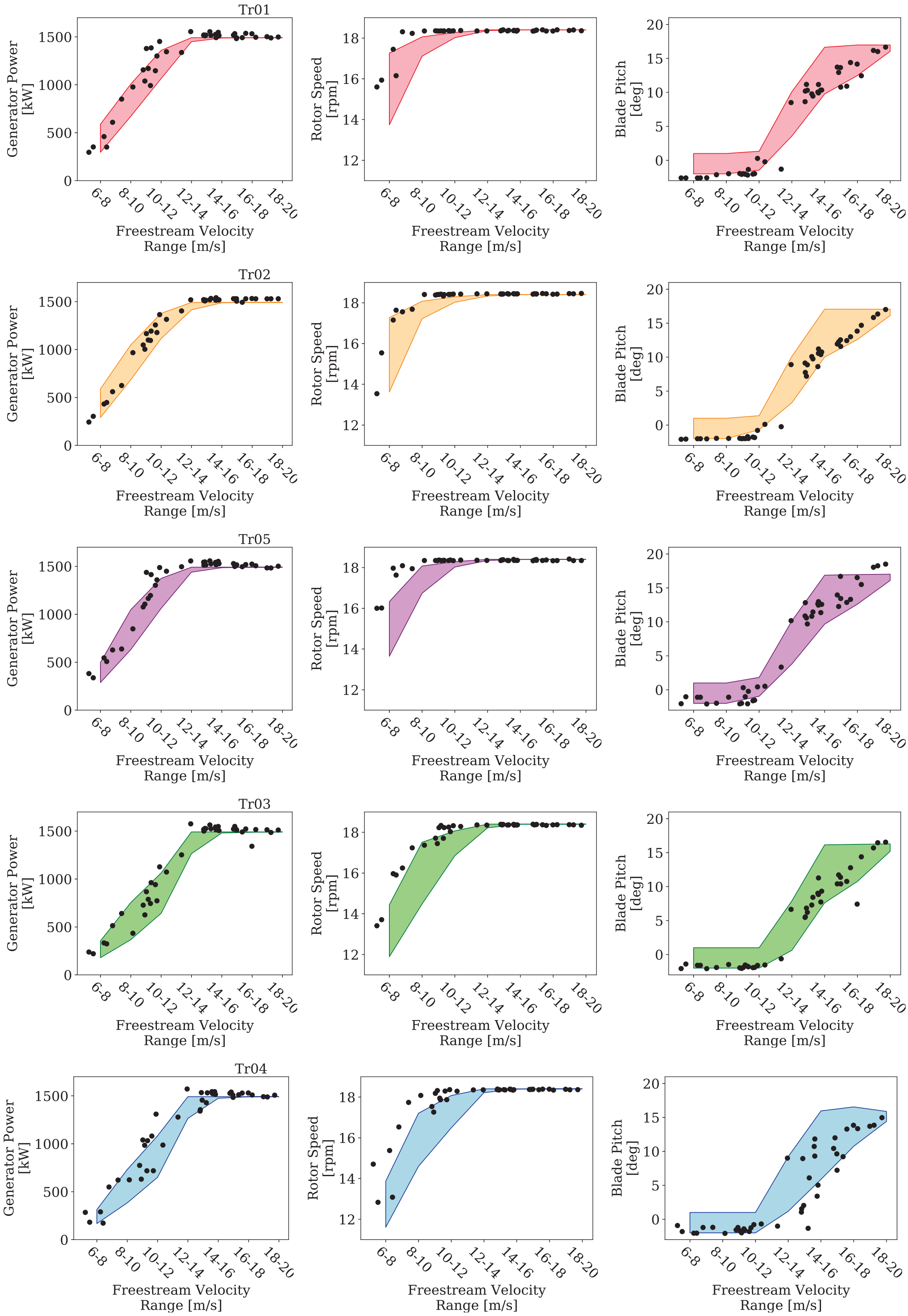


Figure 6. Comparison of measured (dots) and FAST.Farm (shaded region) mean generator power, rotor speed, and blade pitch for all turbines. FAST.Farm results are binned by average inflow wind speed and filled areas show ranges of mean values over all cases and seeds. Turbines results are ordered such that non-wake turbine responses (Tr01, Tr02, and Tr05) are at the top and waked turbine responses (Tr03 and Tr04) are at the bottom.

turbine. The outliers are most prevalent for unwaked turbine Tr05 and waked turbine Tr04. Differences for unwaked turbine Tr05 are likely the result of wind nonhomogeneity across the wind farm—the mean wind speed is likely higher to the east of the wind measurement location. Differences for waked turbine Tr04 (waked behind turbines Tr02 and Tr03) could be the result of wake error buildup down the row. However, it is difficult to determine whether the error is a result of inaccuracies in the controller or wake model. Future comparisons of wake meandering between experimental data and FAST.Farm results will aid in determining the root cause of these differences.

Shown in Figures 7(a,d,e) are bin-averaged FAST.Farm and measured data results for each turbine—i.e., the mean of the means within each 2-m/s bin. Figures 7(b) and (d) shows percent errors between experimental data and FAST.Farm results. Figure 7(f) shows the absolute difference between FAST.Farm and experimental blade pitch results. A different error metric is used for blade pitch because the near-zero blade pitch values artificially inflating the percent error. Bins include between 2 and 11 experimental cases, which could contribute to differences. Overall, the results are quite consistent with those of Figure 6, but provide additional insight. In particular, the line connecting the results for turbines Tr02, Tr03, and Tr04 show the loss in power down the row resulting from the wake of upstream turbines. Again, FAST.Farm predicts a lower mean rotor speed and higher mean pitch angle than the data at below-rated with speeds, with rotor speed percent errors reaching 15%. These discrepancies suggest inaccuracies with the simulated generic controller. This does not seem to have a strong impact on the generator power, with a maximum percent error of 21.5% at below-rated wind speeds but averaging 6.5% for all turbines and bins. This data shows that FAST.Farm predicts a stronger wake impact on the downstream turbines than the data at the lowest wind speeds. Otherwise, there is reasonable agreement between FAST.Farm and the measured data for the power loss down the row. FAST.Farm predicts consistent mean power for the unwaked turbines—Tr01, Tr02, and Tr05. The measured data have some variability, with Tr05 generally predicting higher power than Tr01 and Tr02. Again, this is likely a result of nonhomogeneity of the wind across the real wind farm, which is not captured by the synthetic turbulence used within FAST.Farm.

Shown in Figure 8 are measured standard deviations of 10-minute time-series periods for generator power, rotor speed, and blade pitch for each wind turbine and each case. As in Figure 6, the standard deviation results from FAST.Farm are shown here by the filled areas that encompass the full range of values across all cases and seeds, binned in 2-m/s intervals. It is possible to compare standard deviations in addition to means because FAST.Farm solves the transient dynamics of the wind farm. As was the case for the mean results, it is noted that most of the variation (range) results from the variation across simulation cases, not by varying the turbulence seed. FAST.Farm results show larger rotor speed standard deviation values for below-rated wind speeds than above-rated wind speeds, especially for the waked turbines Tr03 and Tr04. This same tend is seen in the experimental data, but overall FAST.Farm standard deviations are higher. The opposite is true for blade pitch, which shows larger standard deviation values for above-rated wind speeds. This is expected because of the variable speed below rated and variable pitch above rated. This same tend is seen in the experimental data, which closely matches the FAST.Farm results, especially at above-rated wind speeds. At higher wind speeds, FAST.Farm predicts higher rotor speed standard deviations than the data, likely resulting from inaccuracies in the simulated generic controller. For generator power, the range is smallest above rated because of the general lack of variation in this operating region. FAST.Farm generally agrees well with generator power standard deviations at below-rated wind speeds and underpredicts standard deviations at above-rated wind speeds, again likely resulting from inaccuracies in the simulated generic controller. From these generator power and rotor speed standard deviation differences, it appears that the real controller in the field applies a torque controller above rated to finely regulate the rotor speed at the expense of generator power variations. This regulation

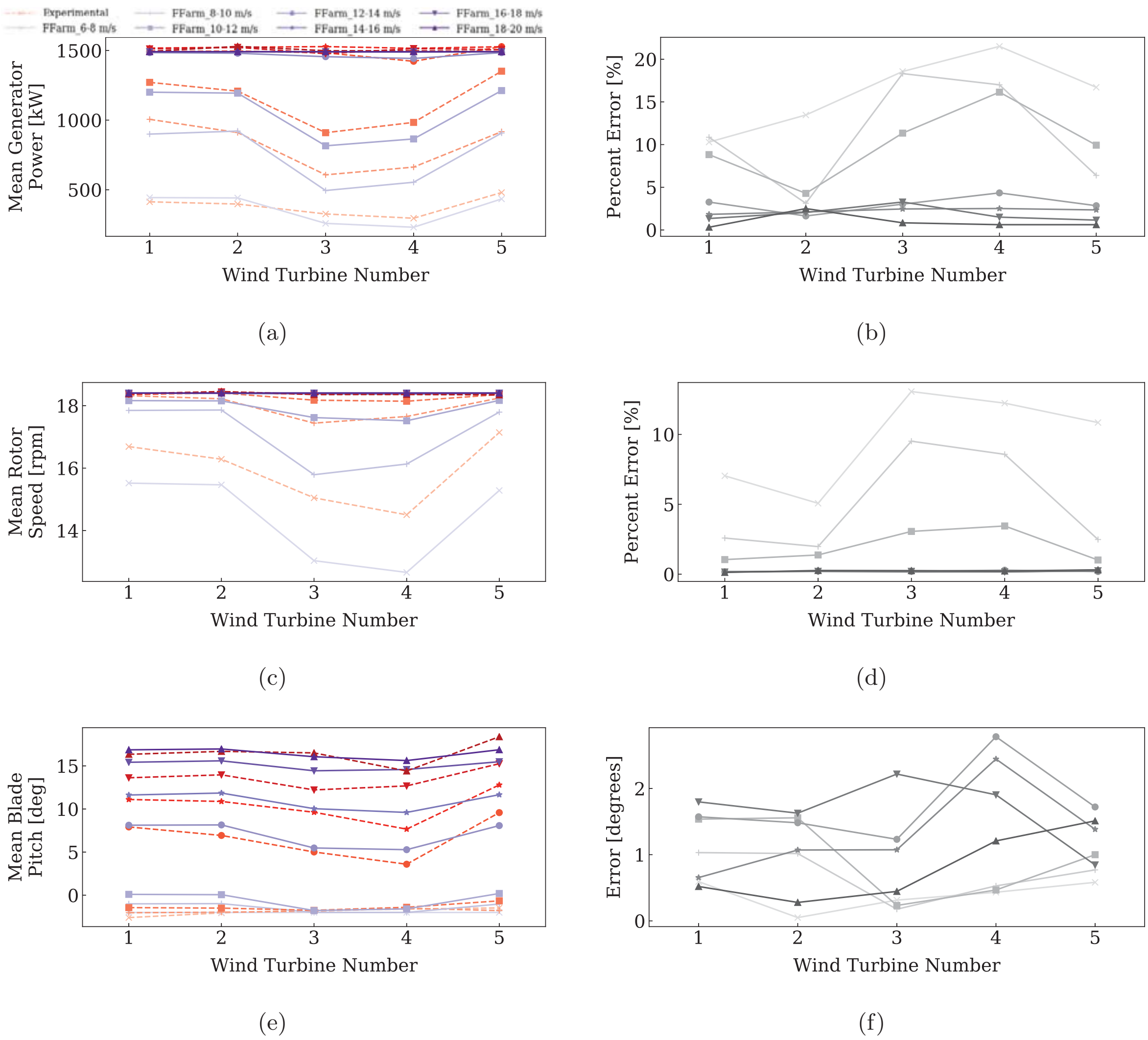


Figure 7. Comparison of measured and FAST.Farm average (a,b) generator power, (c,d) rotor speed, and (e,f) blade pitch for all cases, binned by average inflow wind speed. Error values are shown on the right (b, d, f). For all plots, orange, purple, and grey lines are used for experimental data, FAST.Farm results, and percent errors, respectively. Different symbols and shades are used to distinguish between bins, where lighter shades denote lower inflow wind speed values.

does not apply to Tr02. For all turbines except Tr05, generator power standard deviations tend to increase with increasing wind speed until rated wind speed is reached. At this point, standard deviations tend to lessen. However, experimental measurements for Tr05 show relatively constant standard deviation values for all inflow wind velocities. This does not match FAST.Farm results, which predict a similar trend to the other simulated turbines. It is unclear at this time why Tr05 measurements show a different behavior relative to the surrounding turbines.

4. Discussion and Conclusions

The purpose of this study was to assess the ability of FAST.Farm to accurately predict turbine operation in a small wind farm. This was done by comparing FAST.Farm turbine generator

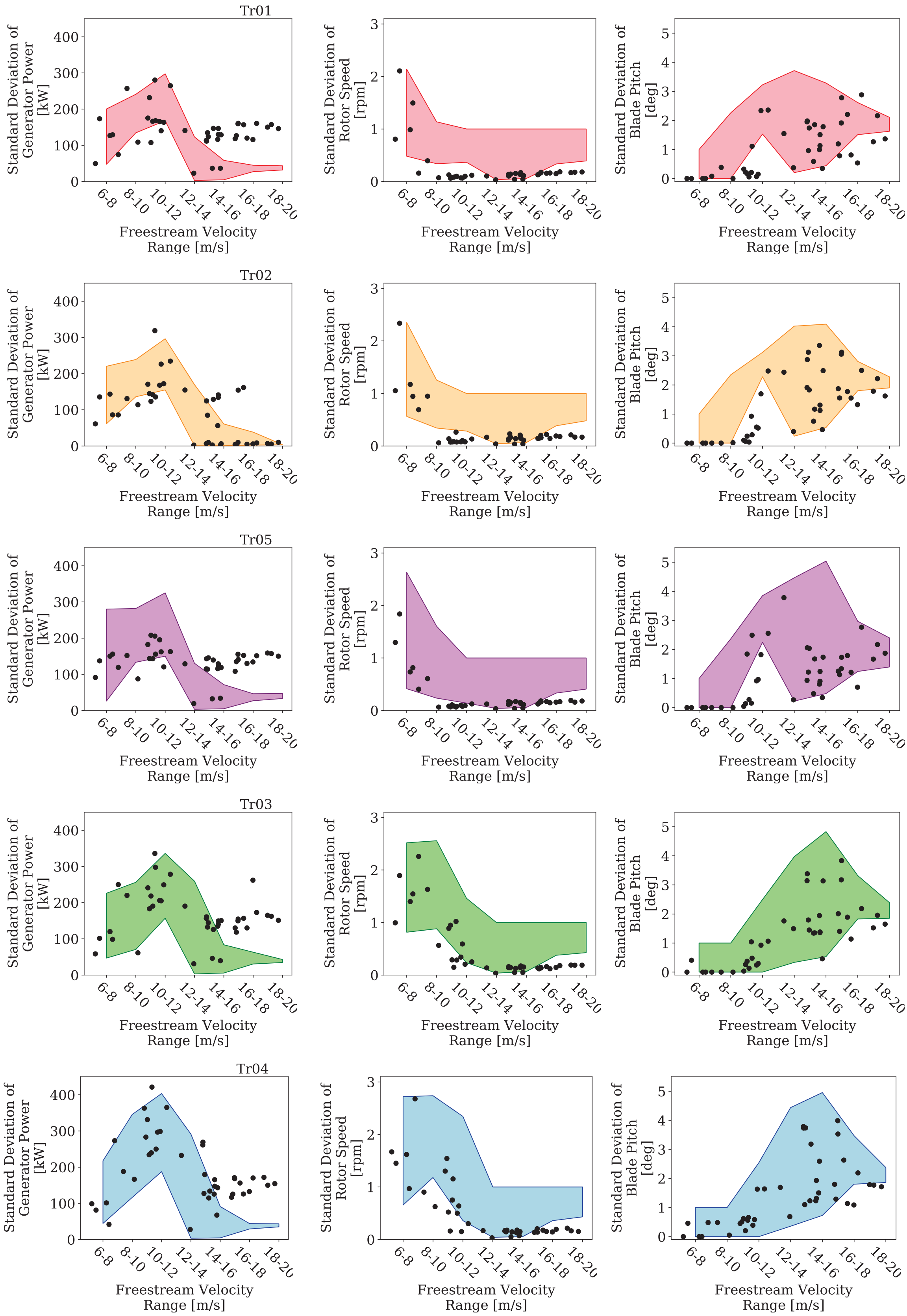


Figure 8. Comparison of measured (dots) and FAST.Farm (shaded regions) generator power, rotor speed, and blade pitch standard deviation. FAST.Farm results are binned by average inflow wind speed and filled areas show ranges of standard deviation values across all cases and seeds. Turbines results are ordered such that non-wake turbine responses (Tr01, Tr02, and Tr05) are at the top and waked turbine responses (Tr03 and Tr04) are at the bottom.

power, rotor speed, and blade pitch for five-turbine simulations to measured SCADA data. It was shown that FAST.Farm tends to predict lower relative generator power at below-rated wind speeds. This difference is likely because of differences in wake development and meandering, resulting from difficulties in accurately modeling atmospheric inflow. However, correct relative generator power trends down the row of three turbines are accurately captured by FAST.Farm, with average percent errors of 6.6% and 7.6% for Tr03 and Tr04, respectively. FAST.Farm generally underpredicts mean rotor speed and overpredicts mean blade pitch at below-rated wind speeds for all turbines. Overprediction of mean blade pitch by FAST.Farm indicates that the blade pitch controller is active at below-rated wind speeds, whereas it is not active in this region for the actual wind farm. This suggests that the generic turbine controller used in the OpenFAST model is not entirely representative of the controller implemented on the real GE 1.5-MW turbines. However, FAST.Farm mean generator power matches measured data for all turbines. For all wind speed bins, percent error of mean generator power averages 6.5%, with a maximum percent error of 21.5% occurring for Tr04 in the wind speeds below 12 m/s. Good agreement is also seen for mean rotor speed and blade pitch at above-rated wind speeds, with an average rotor speed percent error of 0.21%. Standard deviation of blade pitch also matches well, especially at above-rated wind speeds.

The experimental validation clearly shows areas where FAST.Farm does well at predicting the power performance within a small wind farm. Comparisons also indicate a need for more accurate controller models for each turbine in the field campaign. To further investigate differences in downstream turbine response, wake evolution and meandering must be compared to experimental scanning Doppler lidar measurements. This will be studied in future work, in addition to validating FAST.Farm loads against experimental data.

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