Using machine learning to predict wind turbine power output

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Using machine learning to predict wind turbine power output

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Abstract

Wind turbine power output is known to be a strong function of wind speed, but is also affected by turbulence and shear. In this work, new aerostructural simulations of a generic 1.5 MW turbine are used to rank atmospheric influences on power output. Most significant is the hub height wind speed, followed by hub height turbulence intensity and then wind speed shear across the rotor disk. These simulation data are used to train regression trees that predict the turbine response for any combination of wind speed, turbulence intensity, and wind shear that might be expected at a turbine site. For a randomly selected atmospheric condition, the accuracy of the regression tree power predictions is three times higher than that from the traditional power curve methodology. The regression tree method can also be applied to turbine test data and used to predict turbine performance at a new site. No new data are required in comparison to the data that are usually collected for a wind resource assessment. Implementing the method requires turbine manufacturers to create a turbine regression tree model from test site data. Such an approach could significantly reduce bias in power predictions that arise because of the different turbulence and shear at the new site, compared to the test site.

Keywords: machine learning, classification and regression trees, wind energy, wind turbine

1. Introduction

Wind turbines are an important part of the electricity generation portfolio worldwide. In 2011, wind turbines provided 3% of the power generation capacity in the United States, and six US states in the USA met more than 10% of their annual electricity demand through wind energy (Wiser and Bollinger 2012). In that year, the rate of installation of new wind turbine generation capacity was second only to natural gas. Some markets have higher penetration of wind energy; for example, wind turbines provided 3.5% of the energy generated in the European Union in 2008 (European Commission 2011). As a result, it is essential to accurately forecast the output power from wind turbines both before they are installed and once they are operational.

A wind turbine's blades sweep through a circular disk, known as the rotor disk (figure 1). The power output by a wind turbine is a function of the kinetic energy flux through the rotor disk and the efficiency with which that energy can be captured. If the wind has an instantaneous speed u that is uniform throughout a rotor disk of diameter d, the power captured is:

$$P_K = c_p \frac{1}{2} \rho \pi \frac{d^2}{4} u^3, \tag{1}$$

where ρ is the air density and c_p is the 'power coefficient', which describes the fraction of energy that a wind turbine captures. The best theoretical performance of a turbine is the Betz limit, at which $c_p = 16/27$.
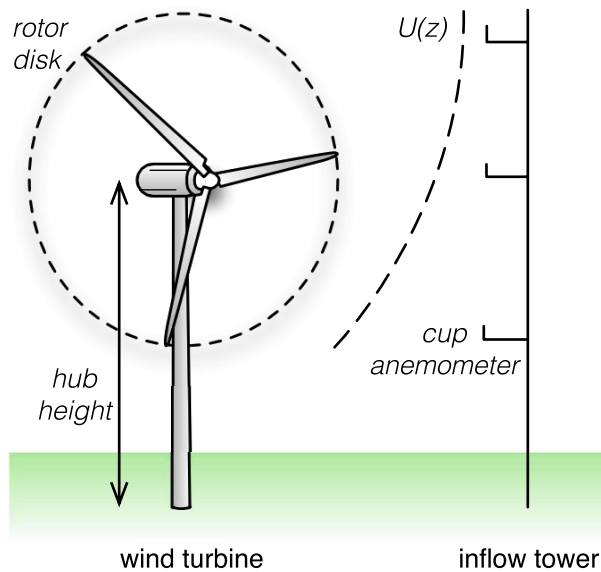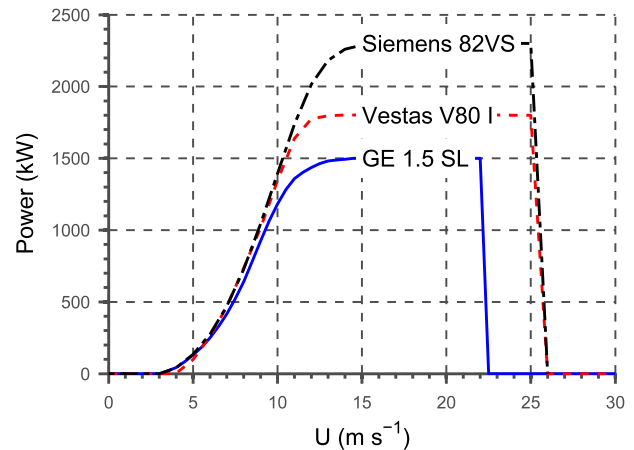
Figure 1. Schematic of wind turbine performance test. Cup anemometers mounted on a mast two to four rotor diameters upwind of the turbine measure wind speed at several heights across the rotor disk, including hub height.

Figure 2. Power curves for several different utility-scale wind turbines. Data are from the manufacturers' power curve tables, collated by Idaho National Laboratory (Seifert 2007).

However, real wind turbines do not achieve this theoretical limit. Their performance is a function of aerodynamics and the need to limit power capture once the rated generator power is reached, at 'rated' wind speed. The generator power, turbine diameter and blade shape are optimized based on site characteristics such as annual average wind speed and the wind speed distribution. Turbine manufacturers measure their turbine's 'power curve'—the relationship between power output and wind speed—at turbine test sites (figure 1). The power curve is calculated from 10 min averaged wind speed ($U = \bar{u}$) and power using methods described in standards (International Electrotechnical Commission 2005). Typical power curves have an s-shape (figure 2), where at wind speeds less than rated the energy capture is approximately proportional to U^3 (known as Region II). At wind speeds above rated, the blade pitch and generator torque are actively controlled to limit the power to the generator's rated power (Region III).

Other metrics provide more information about the inflow characteristics at the test site. Turbulence is quantified by turbulence intensity $Ti = \sigma(u(t))/U$, where $\sigma(u(t))$ is the standard deviation of the wind speed during a 10 min interval. Variation in wind speed with height z can be quantified by fitting the power-law profile $U(z) = \beta z^\alpha$ to measurements. The power-law exponent α is used in this study and the wind industry to quantify wind shear (Brower 2012).

The inverse of the turbine testing process is applied to predict how the same wind turbines will perform at a new site; the wind speed is measured at the turbine hub height and then used to predict power from the power curve. Ti and α are only checked to confirm that the new site is within the limits for the turbine tests.

Any change in the atmosphere that results in a change of the kinetic energy through the turbine rotor disk will potentially impact the power captured (1). Previous studies have shown that variation in atmospheric conditions can lead to changes in turbine power output of 10% or more at the same wind speed (Antoniou *et al* 2009, Wagner *et al* 2011, Hedevang 2012, Vanderwende and Lundquist 2012, Wharton and Lundquist 2012). However, only a few turbine manufacturers provide different power curves for different Ti, suggesting that the effect of turbulence and shear on power output is a recognized effect that is difficult to include in turbine power predictions.

The effects of changes in flow on power capture can be significant. Because of intermittency in the wind, wind turbines typically produce 20%–40% of their maximum possible output over the course of a year. This is known as the capacity factor of the turbine and varies by turbine and site (Manwell *et al* 2009). If a wind turbine has a baseplate capacity of 1.5 MW and a capacity factor of 20%, it will generate 2628 MWh of energy per year. If the energy generated is sold at \$30–\$60 per MWh (Wiser and Bollinger 2012), the loss of just 1% from this turbine compared to predicted power generation represents \$788–\$1577 lost income per year, per turbine. This uncertainty may be particularly important when predicting the power at a potential turbine installation site using local wind speed data. If the amount of energy that is available is over-estimated, the resulting calculation of the cost of electricity may be too optimistic and the site may not be as profitable as expected. Alternatively, underestimating the energy available at a site may mean that the site is not developed at all.

This paper describes how data that are typically collected during testing of a wind turbine may be used to create a more accurate and robust model of the wind turbine energy capture, which can then be used at a new site. Section 2 shows how the energy captured by a generic wind turbine changes with different inflow conditions. In section 3, a machine learning algorithm is introduced that can be used to more accurately predict the energy capture of the wind turbine under differing site conditions. Section 4 discusses potential applications for this technique.

Table 1. Design characteristics of the WindPACT 1.5 MW baseline wind turbine. Sources: Poore and Lettenmaier (2003) and Malcolm and Hansen (2006).

| Parameter	Value
Hub height	84 m
Rotor diameter	70 m
Cut-in speed	3 m s^{-1}
Rated speed	11.5 m s^{-1}
Cut-out speed	27.6 m s^{-1}
Rated power	1.5 MW

2. Response of a wind turbine to turbulence and shear

Wind turbines with a capacity from 1 to 2 MW represented 58% of the total number of turbines over 100 kW that were installed in the United States between 2002 and 2011 (Wiser and Bollinger 2012). Therefore, we use simulations of a generic 1.5 MW wind turbine to show how changes in inflow conditions may impact turbine performance. The turbine design we use is from the Wind Partnerships for Advanced Component Technology (WindPACT) study and is broadly representative of variable speed, variable pitch, 1.5 MW turbines (table 1).

This study uses the FAST aerostructural simulator (Jonkman and Buhl 2005) to simulate the aerodynamic forces on the turbine blades and structure. FAST uses blade-element momentum theory, which is a physically based method that is widely used in the wind industry to create quick and accurate simulations of turbine performance. The aerodynamic lift and drag are calculated at different points along the blade from the incoming wind speed and the blade profile together with look-up tables or simple aerodynamic solvers. As with a real turbine, forces acting on the blade cause rotation of the shaft and deflection of the structure. The rotation is converted into electrical power in a generator. Results from FAST have been validated against data from several wind turbine designs.

For this study, a total of 1796 10 min wind fields were created using the stochastic turbulence simulator, TurbSim (Jonkman 2009, Kelley 2011). TurbSim creates wind fields that include wind shear and turbulence, where the power spectrum of the turbulence approximates the Kaimal spectrum assumed in wind turbine design standards. TurbSim can take target hub height values or profiles of U, α, and Ti as inputs. In this study, wind fields have random combinations of hub height wind speed from 3 to 25 m s^{-1}, hub height turbulence intensity from 5% to 45%, and shear exponent from -0.5 to 0.5. All variables are uniformly randomly distributed over these ranges. These wind fields were then used to force the FAST model of the WindPACT 1.5 MW baseline turbine. A reference set of zero-turbulence simulations with $Ti = 0$% and $\alpha = 0.2$ was also created.

The data from the wind fields from TurbSim and the output from FAST were then processed to form a database of 1796 observations of 10 min average power (the response) as a function of wind speed, turbulence intensity, and shear exponent (the forcing).
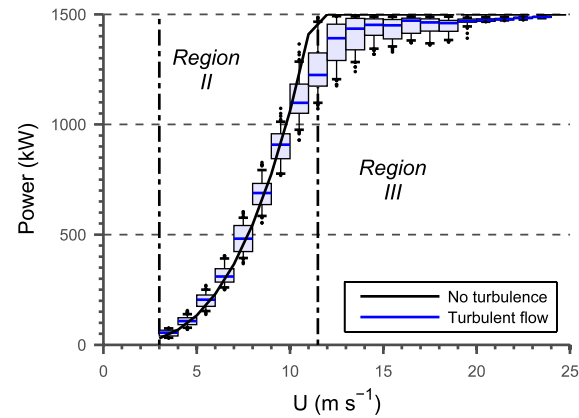

Figure 3. Power curve and operating regions for the WindPACT 1.5 MW turbine. Data are derived from 1796 FAST simulations forced by TurbSim wind fields. Power data are binned into 1 m s^{-1} wind speed bins. The reference zero-turbulence case is plotted together with the data from the turbulent flow fields. The median power produced in the turbulent flow is marked with a horizontal blue line. The box covers the interquartile range. Whiskers extend to the 5th and 95th percentiles, and individual outliers are marked.

Data from the database of simulations can be used to create a power curve by binning the power data into 1 m s^{-1}-wide bins (figure 3). Although the forcing variables are evenly distributed, variance in power is largest near rated wind speed. This sensitivity may result in large variation between predicted power output and observed power output. Furthermore, the mean power generated in simulations that include turbulence is lower than the no-turbulence cases near rated wind speed. The effects of turbulence observed in simulations agree with field studies (e.g. Vanderwende and Lundquist 2012). These results suggest that power predictions at a new site might be biased if the wind conditions (Ti, α and their co-dependency with wind speed U) are different than the test site where the power curve was measured. For example, mountain sites might have quite different characteristics than coastal or inshore sites (e.g. Sathe *et al* 2012, Clifton and Lundquist 2012).

Power output normalized by the zero-turbulence power curve ('normalized power') shows a clear dependence on shear exponent and turbulence intensity (figure 4). At wind speeds below 8 m s^{-1}, power increases with turbulence intensity and shear (figure 4(a)). The increase in power due to turbulence arises because turbulent flow with mean speed U carries more power than laminar flow of the same U, and is well documented in literature (e.g. Wagner *et al* 2010). The changes in power output of ±20% associated with turbulence are approximately half of the change due to a change in wind speed from 7 to 8 m s^{-1} (1).

In contrast, at wind speeds just above and below rated speed (figures 3, 4(b) and (c)), increasing turbulence intensity reduces power output as the turbine cannot capture the extra energy that gusts bring, but a short duration slow down to wind speeds below rated results in a loss of energy. As the mean wind speed increases, the total amount of time with the blades pitched toward feather increases and the wind turbine is more often operating at rated power. At wind speeds much
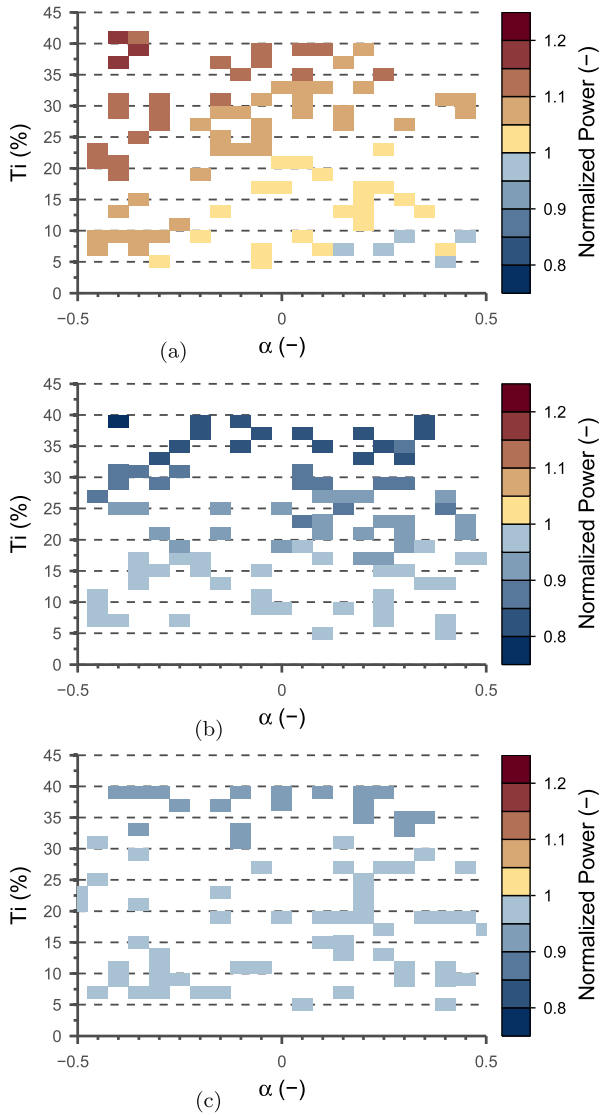
Figure 4. Simulation-derived power output of the WindPACT 1.5 MW wind turbine under different inflow conditions, normalized by the zero-turbulence case. Colors show the median power produced in bins of $Ti = 2\%$ by $\alpha = 0.05$, using the color scale on the right. (a) $7 \le U < 8$ m s^{-1}. (b) $12 \le U < 13$ m s^{-1}. (c) $16 \le U < 17$ m s^{-1}.

greater than rated (figure 4(c)), larger turbulence intensities are required to reduce the output of the machine to less than rated power, regardless of shear. In Regions II and III, variation in *Ti* impacts power performance more than variation in α, as also seen in Wharton and Lundquist (2012).

3. Using machine learning to predict power output in different conditions

3.1. Model design

Currently, we seek a robust method for incorporating turbulence intensity and wind shear into power prediction tools. Just as the database of forcing conditions (hub height wind speed, turbulence intensity, and wind shear) and turbine response (power output) does not contain all possible
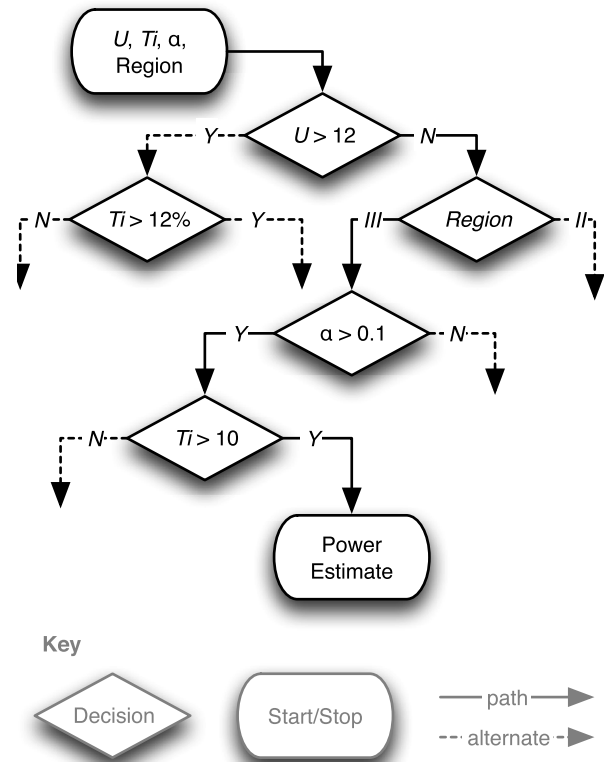
Figure 5. Visualization of the process of predicting the 10 minute mean power for a single observation of U, *Ti*, α and region. The visualization shows one branch of one member of a regression tree. The predictions in this study use an ensemble of 100 regression trees.

combinations of these variables, a turbine test site might not capture all possible combinations that might be found at a new site. Therefore, it is desirable that a method can interpolate between test observations.

The power output from the turbine is not a linear function of wind speed (figure 3), so, multivariate linear regression is not an appropriate technique. Non-linear regression assumes that the relationships are constant throughout the model space (i.e. power output is always proportional to U^n), which from figure 3 is incorrect, so non-linear regression is also inappropriate. Also, multivariate bins only work where the training data includes data in all bins and so would be computationally or observationally more expensive. Instead, a technique is required that can capture non-linear changes in response to forcing. For this reason, we propose a machine learning technique called 'regression trees' (Breiman *et al* 1984) that is implemented in the MATLAB Statistics Toolbox (MATLAB 2010). Regression trees are models that use simple branching question paths to predict an outcome based on inputs. The precise arrangement of the branches depends on the data that are used to train the model. A sketch of one branch of one tree is shown in figure 5, where a prediction of power output is made for a set of forcing conditions. This study uses the mean value predicted by an ensemble of 100 regression trees to increase the accuracy of the power predictions. In the ensemble method, subsets of the training data are used to generate different trees, and power

is calculated using each tree, forced with the same input. The outputs from the 100 different trees are combined to give the mean and variance of the power estimate. An ensemble of trees reduces variance and is less affected by 'noisy' training data, than a single tree.

Hub height wind speed U, hub height turbulence intensity Ti, wind shear exponent α, and operating region are chosen as the predictive variables, while the 10 min mean power is the predicted value. All of these variables can be sampled during turbine testing. Importantly, the predictive variables (U, Ti, α) may be available for a new site if high-frequency hub height wind data are collected at the new location. The turbine operating region can be estimated as a function of mean wind speed and turbine rated speed. Other variables may be important for turbine performance but are not considered in this first exploration of the regression tree method.

### 3.2. Interpolating between observations

The regression tree model can be used to create a similar visualization of the wind turbine performance that was shown in figure 4. Figure 6 shows the modeled effect of shear and turbulence on the 10 min average power at three different hub height wind speeds. Compared to the data shown in figure 4, figure 6 shows clear gradients in power output as a function of turbulence intensity or shear. The authors' experience is that predicting power output for a specific combination of inflow conditions using a regression tree requires approximately one-millionth the CPU hours of a simulation using TurbSim and FAST.

The WindPACT turbine responds differently to changes in shear and turbulence at different wind speeds. In Region II, at wind speeds below 8 m s^{-1} (figure 6(a)), power output increases by up to 10% as turbulence increases or as the magnitude of the shear increases. At wind speeds greater than 8 m s^{-1} and in Region III (figures 6(b) and (c)) the regression tree modeled power is consistent with the simulated power output: power decreases as Ti increases and shows weak or no dependence on shear.

The larger change in power for $|\alpha| > 0.45$ seen in figure 6 suggests a poor performance of the regression tree approach at the edge of the data range. For this reason, the regression tree model should probably only be used where $|\alpha| < 0.45$. The limit on the range of α is due to the range of the training data and is not inherent to the regression tree approach, and shows that users should be careful to check that the test site data captures the range of variability that might be seen at potential deployment sites.

3.3. Predicting turbine response to unseen conditions

The regression tree model can predict the power output by the wind turbine in previously unseen conditions. Predicting energy capture in new conditions ideally requires that the data that were used to train the model encompass the new set of conditions. For example, if the new site has $5 < Ti < 10\%$, and $0.1 < \alpha < 0.2$, it would be ideal if the training data set included data that have the range $3 < Ti < 12\%$ and
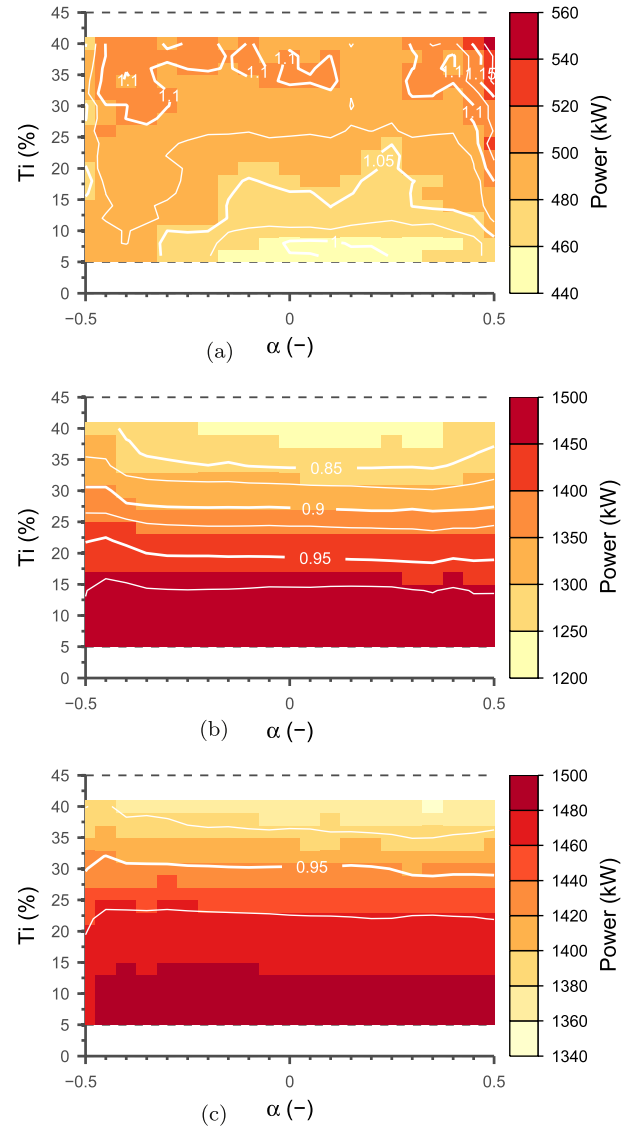
Figure 6. Model-derived power output of the WindPACT 1.5 MW wind turbine under different inflow conditions. Data are shown for a single wind speed in each subfigure. Colors show the median power output in bins of $Ti = 2\%$ by $\alpha = 0.05$, according to the color scale on the right. Contour lines show the power normalized by the zero-turbulence case with $\alpha = 0.2$. The interval between contour lines is 2.5%. (a) $U = 7.5$ m s^{-1}. (b) $U = 12.5$ m s^{-1}. (c) $U = 16.5$ m s^{-1}.

$0.0 < \alpha < 0.25$. This overlap between training and site data is not always possible, and because there may be other factors that affect energy capture, there is some uncertainty in the forecast of power capture. To quantify the accuracy of the energy capture forecast, the 1796 simulations are randomly divided into a 898-member training dataset and a 898-member validation dataset. This random selection is repeated 50 times to give 50 individual test cases. In each test case, the training data is used to create a power curve and to train a regression tree model to predict the 10 min mean power. The power curve is created by calculating the bin-mean power output in 1 m s^{-1}-wide bins from 3 to 4 m s^{-1}, 4–5 m s^{-1}, etc. These models are used to predict the power output (p_i) for each of
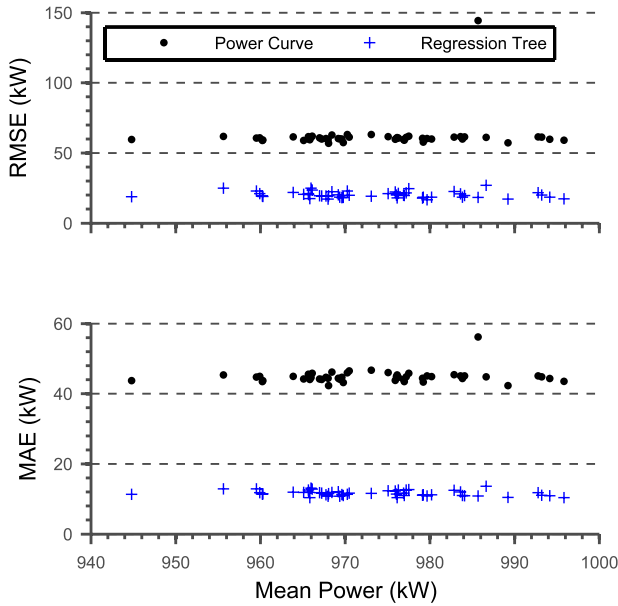
Figure 7. Root-mean-square error (RMSE) and mean absolute error (MAE) for predictions of 10 minute mean power for 50 test cases using the power curve or regression tree approaches. Test cases use training and validation data sets containing half of the 1796 simulations. Data are shown versus the mean power from the simulations in each test case.

the $n = 898$ members of the validation data set. The power output of each member is known from the simulations (P_i). Metrics used to quantify the accuracy of the predicted power from the power curve and regression tree model in each test case include the root-mean-squared error (RMSE) and mean absolute error (MAE):

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left[(p_i - P_i)^2 \right]}, \tag{2}$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |p_i - P_i|. \tag{3}$$

RMSE and MAE are commonly used to judge forecast accuracy. Lower RMSE or MAE indicates better prediction of the turbine response.

Figure 7 summarizes the error metrics for the 50 test cases versus the mean power in each test case. The RMSE and MAE of the power prediction using the power curve derived from binned power data was typically two to three times higher than using the regression tree method. Although the power curve method achieved $R^2 > 0.99$ between predicted and observed power, the regression tree method achieved $R^2 > 0.995$ in all cases (not shown).

4. Discussion

Aerostructural simulations of a generic 1.5 MW wind turbine in a turbulent flow field have been used to quantify that turbine's power output in a range of wind speeds, turbulence intensities and shear. These simulations show

that the response of the turbine is a complex, non-linear function of wind speed, turbulence intensity, and shear. The effect of variations in shear and turbulence intensity is larger below rated speed than at rated wind speeds. At all wind speeds, turbulence has more of an effect on performance than shear. If the WindPACT 1.5 MW behavior is typical of modern turbines, there can be 5–10% variation in 10 min mean power at the same hub height wind speed in typical atmospheric conditions of $5 < Ti < 20\%$ and $-0.1 < \alpha < 0.3$. As conditions vary further, the power output deviates even more. Other atmospheric effects such as directional veer, turbulence kinetic energy, and the presence of a low-level jet and associated coherent structures (e.g. Kelley 2011) may also impact the power output of the wind turbine. The condition of the wind turbine itself may also be important; for example errors in the orientation of the turbine with respect to the wind ('yaw error', e.g. Kragh *et al* 2013), or changes in the turbine control system. The regression tree method could be extended to include other atmospheric effects and more information about the state of the wind turbine if that data were available from more complex simulations, or using data from a turbine test sites such as the National Wind Technology Center in Colorado (Clifton *et al* 2012) or in Europe (e.g. Sathe *et al* 2012).

This study shows that the accuracy of the current power curve method may depend on the distribution of wind speed, turbulence intensity, and shear at the test site, compared to the deployment site. If the test site conditions are similar to the deployment site, the power curve method may give good results. The greatest potential for error when using a power curve approach comes when the test site has high hub height turbulence and high shear compared to the deployment site (figures 4 and 6). In this study, the simulation data have been used to train a regression tree model of the WindPACT 1.5 MW baseline turbine. The regression tree method predicts wind turbine energy capture with two to three times more accuracy than the industry-standard power curve method, and may be more useful for predictions of energy capture at sites that experience different conditions than the test site.

To use the regression tree modeling approach to predict the energy capture of a turbine at a new site, several steps are required. First, a regression tree model of a particular wind turbine is created from test data by the manufacturer or a testing agency. The test data would include inflow data (e.g. U, Ti, and α) and turbine power data, which are all collected during tests that conform to international standards (International Electrotechnical Commission 2005). Then, the same inflow data is measured at the wind turbine deployment site as part of the wind resource assessment process. Usually only one year of data is collected at the deployment site and extrapolated by comparison to a local long-term measurement site to give a prediction of the wind speed for 25 years (Brower 2012). This process of extrapolation is called measure–correlate–predict and is well-defined for wind speed, but there is no well-known method for the extrapolation of shear and turbulence intensity. Instead, it may be necessary to create an artificial 25-year time series of forcing conditions from the site observations (see e.g.

Rose and Apt 2012). Finally, the regression model is forced with the inflow conditions at a new site to estimate the power production over the 25 year period.

As well as predicting the response of a single wind turbine, regression trees could be used to predict energy produced by multiple turbines at a wind plant. The regression tree could be trained using observations of inflow conditions, turbine availability, and power produced by individual turbines. The trained model could then be used to predict power output either for the individual turbines, or for the whole site. Where site data does not include Ti and α, proxies such as time of day, cloud cover or wind direction could be used instead. As with other machine-learning tools applied for meteorological purposes such as Kalman Filters (e.g. Delle Monache *et al* 2011) or artificial neural networks (Barbounis *et al* 2006), the use of a regression tree requires only that the inputs to the tree capture most of the variability of the process, rather than requiring a model that describes the physics. As a result, they are quick to run and easy to update with new information, thus, well-suited to forecasting applications.

5. Conclusions

Simulations of a utility-scale wind turbine have been used to develop a database and to show the complex response of the wind turbine to changes in hub height wind speed, turbulence intensity and rotor disk shear. The database of forcing conditions has been combined with the turbine rated speed to define the turbine operating region. Together, these data were used to generate a regression-tree model of the wind turbine's power generation. The simulations suggest and the model clearly demonstrates that the response of the turbine is a complex non-linear function of hub height wind speed, turbulence intensity, and rotor disk shear. At wind speeds below rated speed, the turbine power output is most sensitive to changes in wind speed and speed, turbulence. At rated speed, the turbine is most sensitive to turbulence intensity and shear, and power can change by 10% under typical atmospheric conditions. At wind speeds greater than rated, the turbine responds most to changes in turbulence intensity.

Predictions of power output using the regression tree model are approximately three times more accurate than power predictions using the power curve. Although this method has been demonstrated using simulated inflow and turbine response data, the method could be used to generate turbine performance models from turbine power testing data. Changes of wind direction with height, non-uniform shear, and the state of the turbine were not considered here but may impact turbine deployment sites, and their effect should be investigated using field data. Application of the data to wind turbine deployment sites does not require any new instrumentation compared to what is currently used. Using this regression tree method helps eliminate biases resulting from deployment site wind conditions (turbulence intensity, shear, and their correlations with wind speed) that differ from the turbine test site.

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