



**DETERMINING THE EFFECTIVE MEAN WIND FOR POWER GENERATION
FROM HIGH-FREQUENCY TURBULENT WIND FLOW MEASUREMENTS**

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Abstract

Using weighted power means, as opposed to arithmetic means, for wind speed statistics is recognized as more relevant to predicting power production from wind turbines. Yet computer models used for hub height wind prediction output arithmetic means, due to the lack of accurate information on wind speed distributions generated by the turbulent flow. The following demonstrates methods used to calculate wind speed statistics using power means, generated from high-frequency (32 Hz) wind measurements, from turbulent flow in the vicinity of a wind turbine array. The dependence of errors, as a function of turbulence intensity, in power production forecasts resulting from the use of arithmetic instead of power means is presented.

1 Introduction

Contemporary meteorological forecast models output mean winds at designated height levels as part of their statistical suite of variables addressing the atmospheric flow. Near the ground, winds are extrapolated down from computed winds aloft to a height at which surface-layer scaling is then applied (often the 10 meter level) to generate near-surface winds. However, because of the evolution of the wind energy industry, there has been particular interest in having a turbine hub-height wind forecast as well (e.g., 80 meters). The winds generated by the models at all levels are presented statistically, namely, a mean wind with possibly associated standard deviations, the latter an implication of the level of turbulence. To obtain a mean wind for the hub-height level it is either explicitly produced as part of the model output (currently rare), or it is extrapolated upward from the 10 meter level predictions through, for example, a power law. These forecast winds are then used by the wind energy industry to predict the amount of power that will be produced at a given site for a given day. The amount of power forecast is in turn traded in the electricity market with the accuracy of the forecast having significant profit implications (Bessa et al., 2011).

Thus, the wind energy industry is motivated to reduce errors in their power forecasts, and one source of error is the limited ability to forecast wind speed distributions (i.e., the characteristics

of local turbulent gusts), and the implied effective mean wind speed relevant to the actual power produced. Since wind turbines do not generate electrical power linearly with the wind speed, with power being produced disproportionately at higher, but less frequent wind velocities, simple arithmetic means can underestimate the amount of power produced. Thus, as an example, in assessing potential wind turbine array sites, preliminary studies are often performed noting the distribution of the local winds. However, the wind speed averages determined from the distributions generally involve time scales much longer than the response times of the turbines. Further, the distributions utilized are often over time periods which smooth diurnal and seasonal variability. This lack of resolution can be a significant source of error in forecasting the amount of power produced.

The following demonstrates methods, using high-resolution wind speed distributions to determine effective mean winds, over short time scales, which can more accurately predict the actual amount of power that would be produced. High-frequency three dimensional wind speed data taken at the Ocotillo Wind Farm near Big Spring, TX (White et al., 2013) is used in the analyses, and, some attempts are made, based on the results, to quantify errors in relation to using arithmetic means to forecast power production. It must be noted that the following treatise is using data taken approximately 50 meters below hub height, and that more accurate results are possible when similar measurements can be made at actual hub-height levels.

2 Analyses

2.1 The Wind Power Equation

The well-known wind power equation is the basis for the discussion. The power P generated by moving air incident on a wind turbine can be described through:

$$P = \frac{1}{2} C_p \eta \rho U^3 A \quad (1)$$

where U is the longitudinal wind speed, ρ is the air density, A is the cross sectional area of the rotors, C_p the turbine power coefficient, and η the mechanical and electrical efficiency factor. The power coefficient C_p has a maximum of 0.59 as described through the Betz limit (Betz, 1920), although in practice, through a number of influences including the characteristics of the turbulent atmospheric flow, the value is closer to 0.40 – 0.45. The efficiency coefficient η for the mechanical and electrical components of the turbine is often near 90% (e.g., RERL/UMA, 2010).

As shown in Equation 1, once the characteristics of the wind turbine are known, power output can be forecast through forecasts of wind speed and air density. However, in relation to the wind speed, simple arithmetic means provide no information on turbulent fluctuations, and the resulting distribution of wind speeds. Actual distributions are expected to be more of the Weibull type rather than Gaussian, the latter of which is assumed in generating an arithmetic mean. Further, because $P \propto U^3$, higher wind speeds contribute nonlinearly more energy. Thus, in order to more accurately forecast power outputs, it is desirable to choose a mean which takes this nonlinearity into account.

2.2 Power Means

A form of averaging utilized in assessing a more accurate forecast of potential wind power is a weighted generalized or power mean:

$$\bar{U}_p = \left(\sum_{i=1}^b w_i x_i^p \right)^{1/p} \quad (2)$$

where (x_1, \dots, x_b) are the bin centers of a wind speed histogram (i.e., the wind speed distribution), with b number of bins, generated from arithmetically averaged winds. The probabilities (w_1, \dots, w_b) associated with each bin involve normalized weighting so that the probabilities sum to unity; that is, $w_i = n_i/N$ where n is the number of values in a particular bin, and N is the total number of shorter time scale wind speed averages present in the distribution. Thus, the overall mean wind \bar{U}_p based on the power p can be calculated from a time series of arithmetically averaged winds.

Currently, in practice, the shorter wind speed averages used in generating the wind speed distributions are calculated over time scales (e.g., 10 to 60 minutes) much greater than the response times of the wind turbines. The response times of the turbines, significantly a function of pitch control on modern variable pitch turbine blades, can be less than a minute if no directional changes in the orientation of the turbine needs to be made. Consequently, because of the use of operational-grade, relatively slow-response anemometry (e.g., cup or propeller anemometers), the needed time resolution in the wind signals is lacking, introducing a limitation for accuracy in forecasting wind power. The current study attempts to increase the accuracy by employing power means for wind power forecasting using high-frequency wind measurements.

2.3 Fast-Response Wind Speed Data

Just upwind of the Ocotillo Wind Farm (32.1203 N, 101.3756 W) near Big Spring, Texas, USA, from August – December 2010, fast-response (32 Hz) wind speed data were taken simultaneously at five height levels near the ground (Vogel et al., 2013; White et al., 2013). Five R. M. Young model 81000 sonic anemometers were mounted on a 30-meter triangular tower at height levels 2.99, 8.51, 14.76, 21.00, 27.40 meters above ground level (AGL). The tower with instrumentation at these levels and others are shown in Figure 1.

Best estimates for land surface characteristics include a canopy height of approximately 3.0 meters, a displacement height of 1.75 meters, and a roughness length of 0.20 meters. Mean canopy heights were measured directly while displacement height and roughness length were determined through vertical wind profile analyses. The 32 Hz measurements include all three components (N-S, E-W, and vertical) of the wind, and temperature. The resulting turbulent flow data is logged continuously so that any size data set, from 1/32 s to the next break in the continuous data (a relatively rare occurrence), can be established on which to operate.

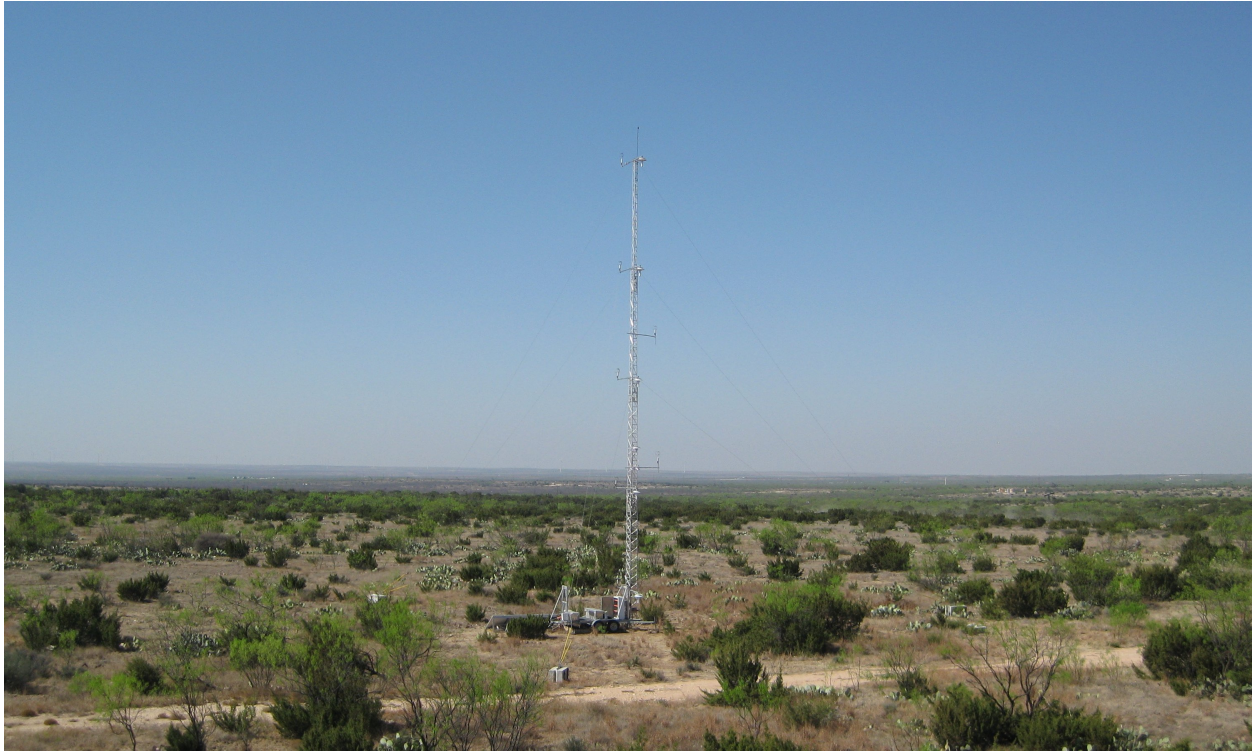


Figure 1: The 30-meter tower used to measure turbulent flow upwind of the Ocotillo wind farm near Big Spring, TX. The view is toward the southwest with the five sonic anemometers used for fast-response measurements mounted on aluminum pipe arms pointing toward the south.

2.4 Data Processing

Once the 32 Hz measurements of the three components of the wind, and temperature, were logged and stored, the data was processed to produce a suite of fundamental mean and turbulence statistics. The standard procedure was to log the data into files 30 minutes in length. For these analyses the 30 minute files were concatenated into 24 hour files to reduce discontinuities in running means used to compute the statistics. Checks were performed prior to concatenation for discontinuities in the data stream, so that no 24 hour files were generated where there were missing data. Once a reduced data set was produced with continuous 24 hour data files the processing involved a sequence of steps:

1. rotate coordinates: a coordinate transformation was performed every 1200 seconds to rotate the wind data from N-S, E-W, and vertical components to longitudinal, transverse, and vertical components. The 1200 second interval seemed a good compromise between too short a period, where relevant fluctuations could be smoothed away, and too long a period, so that steady state conditions might be significantly violated. Further, turbulent kinetic energy (TKE) of the flow was checked prior to, and after, the coordinate rotation to ensure that energy was conserved.
2. calculate statistics: using a 400 second centered, symmetric boxcar running mean, mean

and turbulence statistics were generated for a specified output frequency. The running mean ensures that each data point has a unique average from which to produce the perturbations. Mathematically this can be described as:

$$\mathbf{u}' = \mathbf{u} - \bar{\mathbf{u}} \quad (3)$$

where \mathbf{u} is the one-dimensional array of instantaneous wind speeds, $\bar{\mathbf{u}}$, is the array of means generated from the running mean, and \mathbf{u}' is the resulting array of perturbations.

Previous analyses addressing spectra of the three components of the wind indicate that a running mean period of 400 s is a good estimate of the cospectral gap length (Vogel and Pendergrass, 2012; Vickers and Mahrt, 2003). Note, that as long as one consistently operates on the signals with the same mean removal process, and one has enough values involved in generating the statistics to be considered a large population, that any output frequency of the perturbations is valid.

The statistics calculated include means and variances of the individual signals. As stated, these means could involve data of any length from approximately 1 second ($n > 30$ considered a large population of points) to lengths approaching the limits of steady-state conditions (e.g., of order 1 hour).

2.5 Wind Speed Distributions

Once the data was processed so as to calculate mean flow and turbulence statistics, wind speed distributions could be generated. For example, one could determine mean and turbulence statistics every 15 seconds. This time interval is approximately the same amount of time that the Suzlon S88 turbine blades at Ocotillo complete 4 rotations, although presumably less than the response time of the turbine assembly to fluctuations in the atmospheric flow. It should be noted that actual response times, and actual output power amounts, are proprietary information, and were not available at the time of this writing.

The following briefly describes the process of generating the wind speed distributions and effective power means according to Equation 2. In this analysis only the top level sonic data (27.40 m AGL) was used, since it was closest to the 80 m hub-height level of the turbines. This analysis demonstrates the method and quantifies potential errors, however, as stated, a more accurate assessment would involve measurements just upwind of the turbine array, but at actual hub height.

Using the 27.40 m longitudinal wind speed data for a particular specified statistics averaging time (e.g., 15 seconds), a series of files, each involving a 24 hour measurement period, was generated. Somewhat arbitrarily chosen for ease of use in the analysis, these files encompassed data from 1200 UTC (0600 LST) to 1200 UTC the following day. Of particular interest was the time period from 0600 LST to 1700 LST, since this time period corresponds to a period close to that of the daytime time range that U. S. energy companies use to sell its wind-generated power. Thus, wind speed distributions were computed for every hour, within the 0600 to 1700 LST time period, for

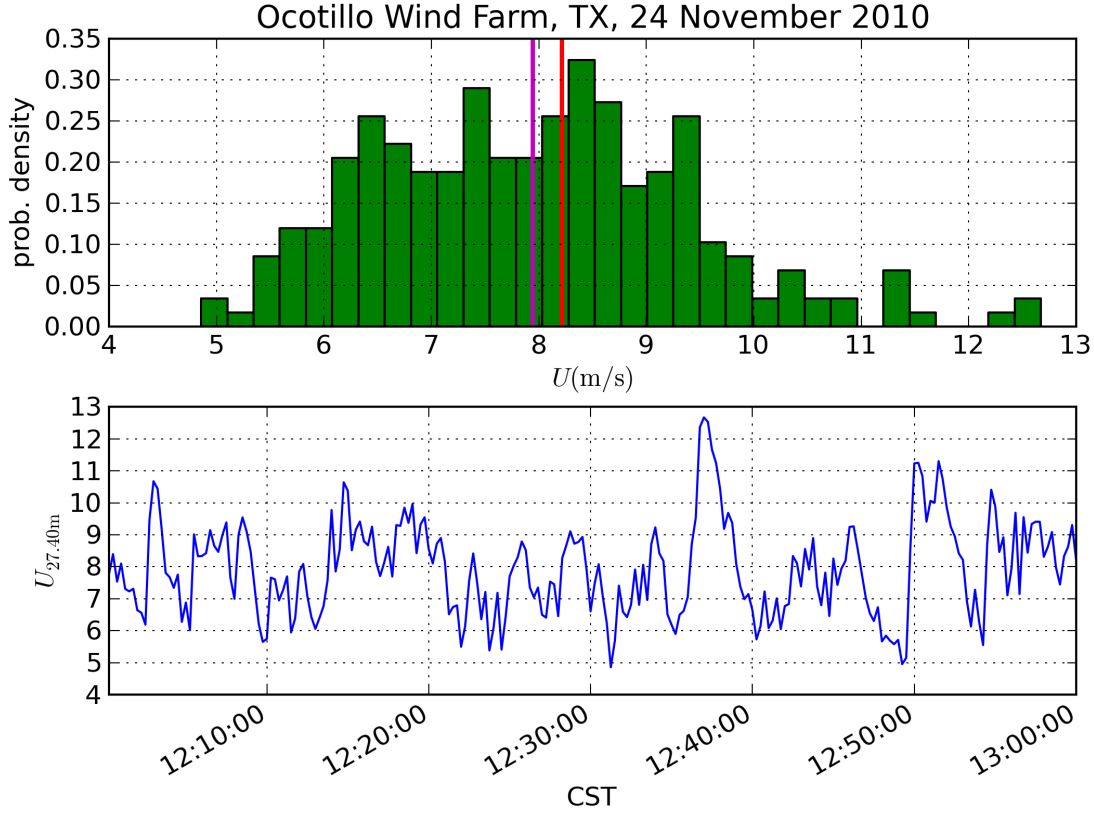


Figure 2: A wind speed distribution from 24 November 2010, 1200-1300 local standard time, of 15 second arithmetically averaged longitudinal winds, at a height of 27.40 m AGL, upwind of the Ocotillo Wind Farm near Big Spring, Texas USA. The lower plot shows the wind speed signal, the upper plot shows the probability density for 32 wind speed bins with the magenta line (—) giving the arithmetic average of 7.94 m/s for the distribution, and the red line (—) giving the weighted power mean of 8.21 m/s.

every 24 hour period of continuous data available (39 days), using arithmetically averaged wind speeds according to a specified averaging time.

More specifically, for each 1 hour period, a time series of average wind speeds $\hat{\mathbf{u}}$ (again, e.g., 15 seconds) was used to generate a histogram as shown in Figure 2. The histogram consists of probability densities described through,

$$\text{probability density} = \frac{n}{\text{len}(\hat{\mathbf{u}}) \cdot \Delta\text{bin}} \quad (4)$$

where n is the number of occurrences for a particular bin, $\text{len}(\hat{\mathbf{u}})$ is the length of the wind speed time series, and Δbin is the bin width in m/s. The probability densities multiplied by the bin width give the weights to determine a weighted power mean according to Equation 2.

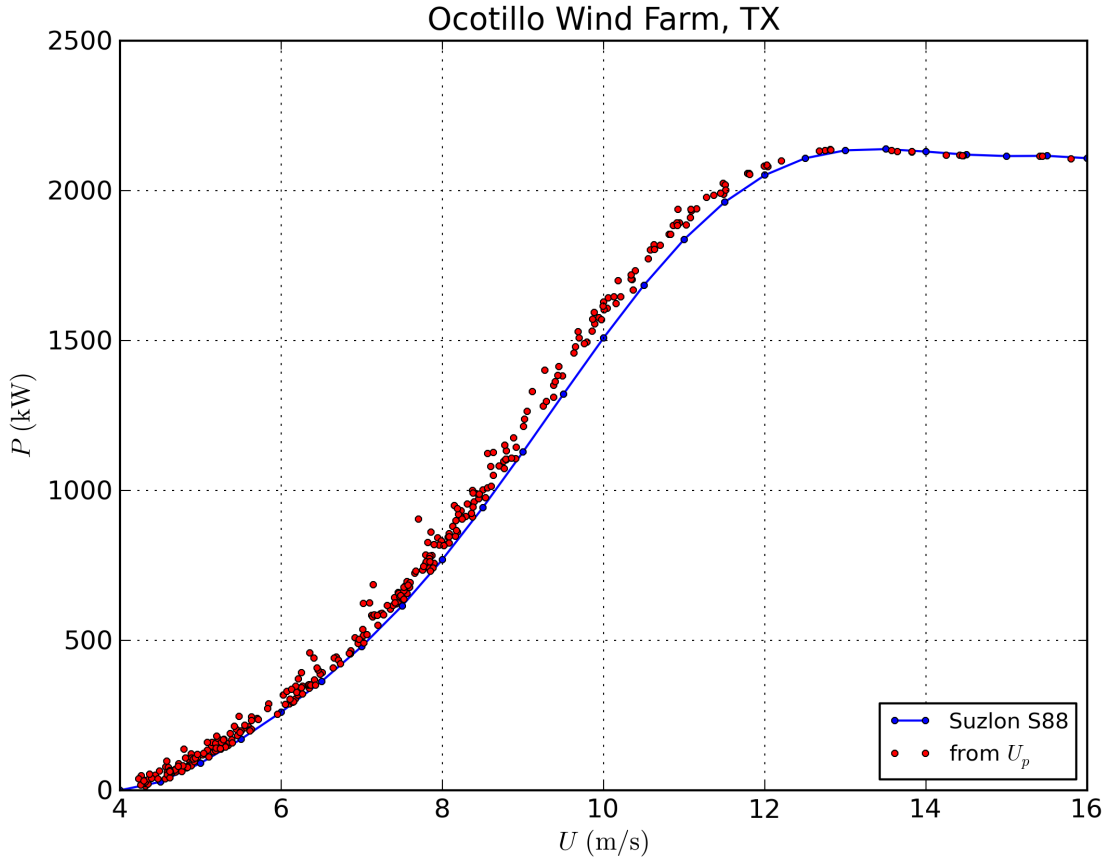


Figure 3: A manufacturer supplied power curve for a Suzlon S88 2.1 MW turbine, and power amounts inferred using a weighted power mean for 1-hour wind distributions. The power means in this case were calculated using 15 second arithmetically averaged winds. The data show the increased amount of predicted power (using the supplied power curve) that could be calculated if power means were used as opposed to arithmetically averaged 1-hour winds.

2.6 Power Estimates

Once the 1-hour weighted power means were calculated from the shorter time scale wind speed distribution, estimated wind power amounts can be calculated based on a power curve for the wind turbine used. Figure 3 illustrates this using our example of wind distributions of 15 second arithmetically averaged winds. The data shown are inferred power amounts, based on weighted power means of 1 hour wind distributions, using the manufacturer-supplied power curve (Suzlon, 2011) for the Suzlon S88 2.1 MW turbines present at Ocotillo Wind Farm. Note the increased amount of predicted power evident through use of these means rather than those produced from the arithmetically averaged winds (i.e., the blue curve).

In similar fashion one could produce inferred power amounts for different short-time-scale averaging times to see the effect of smoothing out turbulent fluctuations on the potential power produced.

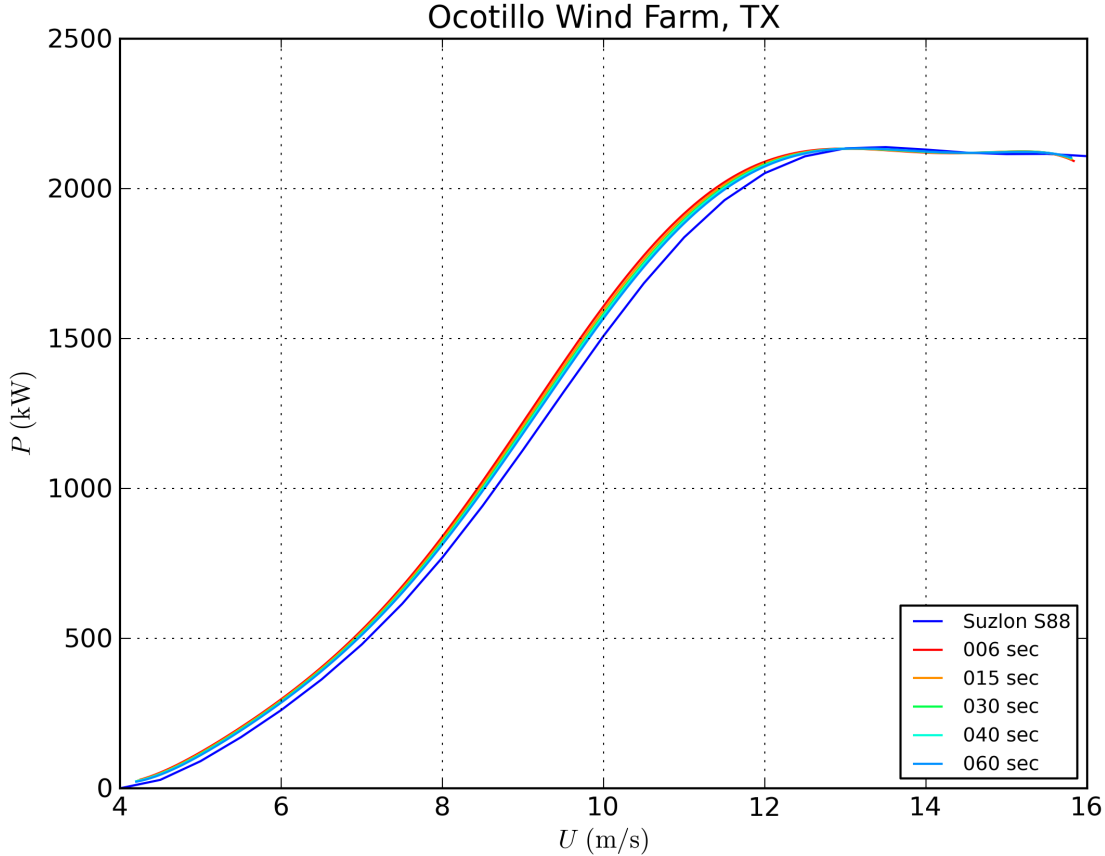


Figure 4: The power curve for the Suzlon S88 wind turbine along with curves showing the increased amount of predicted power for 5 different short term wind averaging times. Not including the S88 power curve, the curves shown are those fitted to power estimates based on the power means for wind speed U_p . A higher-order polynomial was used to generate the fits.

Figure 4 shows curves fitted to calculated power data from the 1-hour wind speed distributions similar to Figure 3 but for different wind speed averaging times. As would be expected, the longer the averaging times the closer the curves approach the Suzlon turbine curve, which in this analysis, we assume to be the exact inferred power amounts corresponding to the 1-hour arithmetic mean wind values.

Finally, it is useful to observe the normalized differences between the inferred wind power, generated using a 1-hour arithmetic mean wind, versus a 1-hour weighted power mean wind, as a function of turbulence intensity. Figure 5 shows plots comparing the relative difference in power generated using a 1-hour arithmetic mean wind P_l , and power generated using a 1-hour weighted power mean wind P_d for 6, 15, 30 and 60 second wind averaging times. Here we have used the subscript l to denote that a linear (arithmetic) average was utilized, and the subscript d to infer that a weighted power mean, determined from a wind speed distribution, was used. The plots show that for the short-time-scales averaging used to generate the distributions, as turbulence intensity

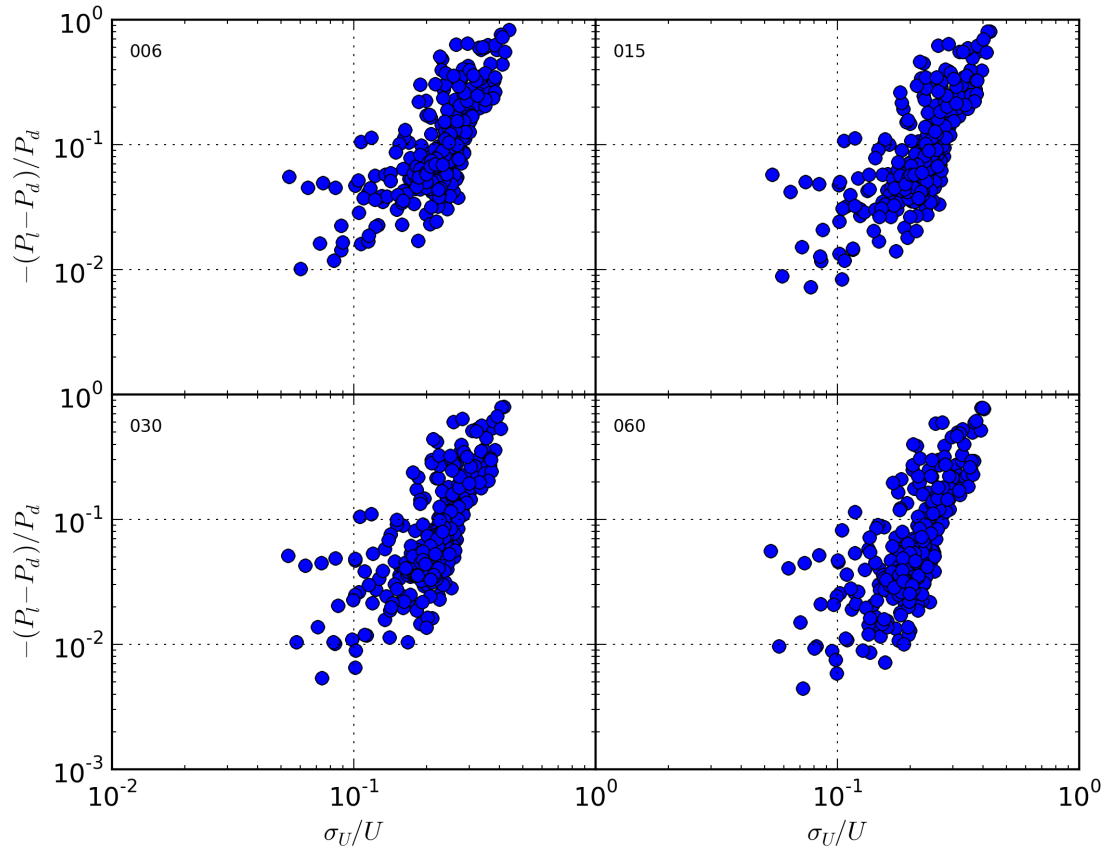


Figure 5: The relative difference, as a function of turbulence intensity, in potential power generated using a 1-hour arithmetic mean wind P_l versus a 1-hour weighted power mean wind P_d , for 6, 15, 30 and 60 second wind averaging times. This representation shows the negative of the underestimates to enable logarithmic scaling. Note the increase in the overall underestimate of power as one moves to higher turbulence intensities, and from longer to shorter wind averaging times.

increases, the underestimations in power do as well. Also, as one moves from a longer time averaging of 60 seconds to shorter averaging times, the magnitudes of the underestimates increases. For these four averaging times the fraction of cases underestimating 10% or greater range from 29% for 60 sec to 40% for 6 sec. This demonstrates in part the effect of significantly underestimating the amount of power that will be produced by smoothing out the turbulent gusts evident in higher frequency wind measurements.

3 Summary

This paper demonstrates one method to assess the underestimation of forecasted power produced by wind turbines because of the use of forecasted arithmetically averaged winds, which contain no

turbulence information. It has been recognized that a weighted power mean wind is a more appropriate quantity to address the amount of wind power produced, however, power means, derived from shorter-time-scale, arithmetically averaged winds have rarely been applied using mean winds on time scales near the response times of wind turbines. Limitations to the current methods include that the measurements were not conducted at actual turbine hub-height level, and that comparisons were made to smoothed, manufacturer-supplied, power curves for the turbines. A more relevant study would involve measurements at hub height, and actual calculations of 1-hour potential wind power through Equation 1. The latter would use measurements of air density and wind speeds, and use accurate values for the coefficients C_p and η , and the cross-sectional area of the turbine blades A . These calculated values could then be compared to actual power amounts generated, if a power company were to release such proprietary data. In the meantime, the current analysis can be useful to begin to quantify a source of error in forecasting wind power. If turbulence information such as wind speed variance was generated in forecast models along with mean winds, the mean winds could potentially be adjusted according to relationships such as those presented in Figure 5. In any case, as the response times of the wind turbines improve, the importance of the inclusion of information on short-time-scale turbulent gusts in a forecast of winds relevant to power production increases, and the wind power industry may look to revise current forecast methods to incorporate the added information.

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