An Evaluation of Advanced Tools for Distributed Wind Turbine Performance Estimation

Preprint

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An Evaluation of Advanced Tools for Distributed Wind Turbine Performance Estimation

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Abstract. We evaluate various classes of distributed wind turbine performance tools across two sites in the United States. The class of tools ranges from the simple mass conservation model to the coupled Reynolds-averaged Navier-Stokes model, all initiated by the WIND Toolkit data set. The resource estimation at the site is evaluated against measured data at the mast location. Taking a sample 100-kW wind turbine and constant losses, we evaluate Openwind, Continuum, and WindNinja tools and document annual energy production (AEP) and time-series statistics associated with the performance estimation of the wind turbine. Using a methodology that is consistent and unbiased across the three options currently available in the industry, we elaborate results at the two sample locations and discuss the probable sources of discrepancy in the AEP estimates. Two main sources of the discrepancy come from the input WIND Toolkit data and the spatial modeling techniques of the tools to capture atmospheric physics. The discussion includes additional values that these tools may bring into the energy assessment process to enhance the owners' confidence over the distributed wind power systems.

1. Introduction

Small- and medium-scale wind power system projects [1] may not always afford a detailed wind-resource measurement campaign for various reasons. Often, such projects rely on wind resource maps such as the National Renewable Energy Laboratory (NREL) Wind Prospector [2], modeled time-series data (e.g., Wind Integration National Dataset (WIND) Toolkit, MERRA-2, University Corporation for Atmospheric Research (UCAR), National Aeronautics and Space Administration (NASA) Surface Meteorology), or resource estimates that prospective turbine vendors offer along with a sales proposal. The performance estimate based on such data sets may not always provide an accurate estimate, and it comes with a wide range of uncertainties. These uncertainties can have impacts on the cost of financing as well as on the owner's confidence over the wind power system among alternative options. This effort will compare the performance prediction from three typical modeling approaches to long-term data collected at two specific locations with different site characteristics. This paper summarizes an effort, under a new U.S. Department of Energy Tools Assessing Performance project, to understand the capabilities of wind resource tools from the viewpoint of the distributed wind energy industry.

The WIND Toolkit was developed by NREL to support the next generation of wind integration studies [3]. This data set builds on the Eastern Wind Integration Data Set produced earlier by AWS Truepower and Western Wind Integration Data Set by 3TIER [4]. The WIND Toolkit [5] data set was generated on a 2-km-by-2-km grid for the entire United States. The vertical resolution is 20 m, and data points range from the ground to 200 m above ground level (AGL). The temporal resolution of data is 5 minutes, and the time span ranges from 2007 to 2013. The public version of the example WIND Toolkit data set provides a time series of the wind resource at various heights at about 126,000 data points across the United States and has undergone extensive inhouse cross-validation. The data set for these sites can be accessed through a web interface using an application programming interface. A subset of WIND Toolkit sites is accessible through the NREL Wind Prospector [4]. We use the WIND Toolkit data set as a baseline input for evaluating the tools.

2. Problem Statement

It is common across the distributed wind industry to use publicly available modeled data sources, either directly or in combination with siting tools, to assess the expected annual energy production (AEP) of distributed wind turbines [5]. Understanding the accuracy of these predictions impacts potential project development, and the energy assessment process entails addressing multiple types of uncertainties. The first type of uncertainty is related to the input data, which in this study came from the WIND Toolkit data set. The second type includes uncertainty associated with the wind flow-modeling approach used in the tool. Additional uncertainty is introduced when the wind-speed numbers are converted to energy estimates. The greatest source of uncertainty was related to the input data. The problem is illustrated here by estimating wind speed and simulated turbine performance for two example sites—the first in Colorado at NREL's Flatirons Campus and the second in Washington State at the Hanford Meteorological Station—comparing information to the WIND Toolkit data set and various classes of wind flow models.

In this analysis, we compare performance to the closest WIND Toolkit data point but also use those data as inputs to the various flow models, which is commonly done by the distributed wind industry. Our motivation is to understand spatial modeling capabilities of industry standards tools so as to estimate the wind resource at neighborhood locations of WIND Toolkit points. Many studies have compared the performance of wind flow models [6, 7] for utility-scale application. This study, however, focuses more on the near-surface layer (~40 m AGL) of the atmospheric boundary layer, with a different set of inputs more applicable to the distributed wind power industry [8].

3. Sites Description

The two sites in this study are in Boulder, Colorado, and Benton County, Washington. The Boulder site at NREL's Flatirons Campus uses NREL's M2 meteorological tower [9]. The NREL M2 site is surrounded by three public WIND Toolkit points—Site IDs WTK 01:50009, WTK 02:50135, and WTK 03:50136, see Figure 1—with the WTK 01 site being the closest.

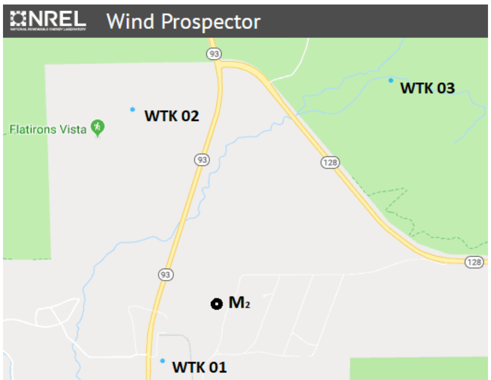

Figure 1. The NREL M2 site location south of Boulder, Colorado, with three associated local WTK modeling points.

The Hanford Meteorological Station site, Station# 21, is a 120-m-tall station in Benton County, Washington [10]. This site is shown in Figure 2. For the Hanford site, the nearest grid points via Wind Prospector (Site ID: 123265) are about 6.92 km south of the site. Hence, we had to download the data directly from the NREL WIND Toolkit database using an application programming interface. The evaluation at this site is based on the four neighboring points (HFWTK01, HFWTK02, HFWTK03, and HFWTK04) shown in Figure 3.

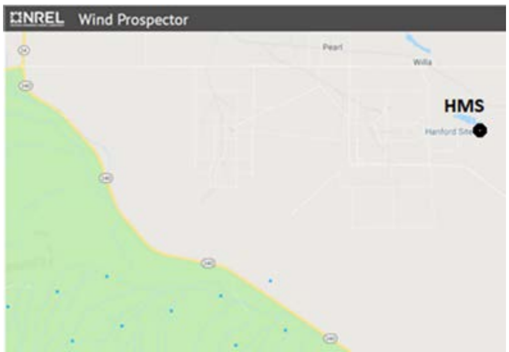

Figure 2. The Hanford site located in Benton County, Washington.

Figure 3. The Hanford site and four associated WIND Toolkit points.

4. Methodology

All three of the identified tools use, to the extent possible, the same set of inputs. GIS inputs come from the U.S. Geological Survey national map, and the U.S. Geological Survey 30-m digital elevation model data set is used for topographic information. The land-cover code has been reclassified to roughness length and displacement heights following the best practices of wind resource modeling. Only a few sets of obstacles around the test site have been considered for simplicity; however, it is consistent across all tools. As stated, WIND Toolkit data were used as source input for the models.

4.1. Description of software and versions

We use three classes of wind flow models. The representative model for the mass-conservation model is Openwind [11]. For the reduced-order model class, we used Continuum [12], and for a coupled computational fluid dynamics (CFD) model, we used the Reynolds-averaged Navier-Stokes (RANS)-based WindNinja [13]. Openwind and Continuum represent industry usage, whereas WindNinja, which uses the OpenFOAM solver, represents academia usage.

4.1.1. Openwind

Openwind is a wind farm design and optimization software developed by AWS Truepower, now an Underwriters Laboratories (UL) company. The theory underlying Openwind is summarized in part in Ref [14]. Openwind uses a mass-consistent wind flow model. This software tries to capture as many aspects of wind farm design and has an easy-to-use GIS interface. It can output general AEP statistics as well as time series of energy capture for each turbine.

4.1.2. Continuum

Continuum uses a wind flow model based on an approximation of the RANS momentum equation. This wind flow model was awarded a U.S. patent in 2013. A physical quantity— "exposure"—derived from the topography is used to estimate wind speed at a point relative to the reference location. Exposure is a function of elevation difference between the given point and the surrounding terrain, weighted by the inverse of the distance between the points. For this study, we used Continuum version 2.3, which does not output time series of energy.

4.1.3. WindNinja

WindNinja is a wind flow model developed and maintained by the U.S. Forest Service Missoula Fire Sciences Laboratory [15]. It computes spatially varying wind fields for wildland fire application. WindNinja uses a standard CFD OpenFOAM [16] solver and can also use weather model data from an external source. Derived from OpenFOAM, WindNinja solver has an option to solve mass-conservation equations or both mass- and momentum-conservation equations. WindNinja 3.5.2 was used for this study.

Here, we report the steady-state solutions for each hourly time stamp for 2013. The grid spacing is about 91 m in a 10-km-by-8-km computational domain. There are 18 vertical levels, with the nearest being about 2 m and the farthest about 1000 m from the ground. The time-series data are computed using the mass-conservation model. In the case of WIND Toolkit, WindNinja, and the measured data, the hourly time series of wind speed was fed through the power curve of the wind turbine to estimate energy assessment.

4.2. Time-Series Comparison

Among the tools considered, Openwind and WindNinja tools can output time series of wind speed at the target location. For time-series output, we also compared the coefficient of determination, commonly known as R^2. R^2 is computed using Equation (1) with measured time series (y) and synthesized time series ($\hat{y}$). This coefficient quantifies the proportion of the variance explained by the measured data. We computed R^2 for both monthly and daily averaged time series. An alternative metric to compare time series is goodness of fit (FIT). FIT is computed using Equation (2), which is based on the L^2 -norm:

$$R^2 = 1 - \frac{\sum(y-\hat{y})^2}{\sum(y-\bar{y})^2} \quad (1)$$

$$\text{FIT} = \left[1 - \frac{NORM(y-\hat{y})}{NORM\ (y-\bar{y})}\right] \times 100\ \% \quad (2)$$

Openwind can also provide a time series of energy capture. For these two tools, we have computed R^2 as well as the FIT compared with the measured data at the site.

5. Test Wind Turbine

This study uses an NPS100C-24 wind turbine from Northern Power System [17], which is a 100-kW Class III/A wind turbine with a 24-m rotor diameter and a nominal hub height of 37 m. We corrected the power curve to consider the effect of elevation and assumed standard losses as follows: availability (6%), turbine performance (4%), and other losses (4%).

The cut-in, rated, and cut-out wind speeds for the turbine are about 3, 13, and 25 m/s, respectively, as shown in the turbine power curve in Figure 4. We used the power curve with wind-speed resolution of 0.1 m/s to compute energy estimates.

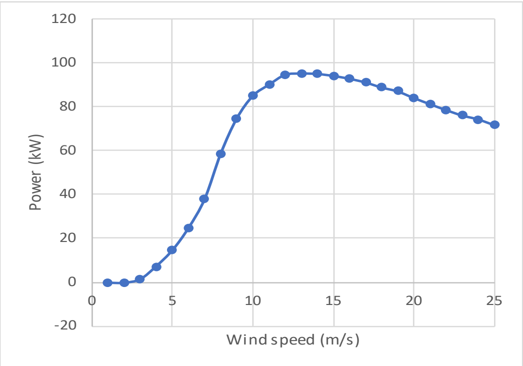

Figure 4. NPS 100-24 power curve at standard temperature and pressure.

6. Model input data

A microscale wind flow model tries to capture fine-scale wind primarily resulting from, among other things, the effect of terrain, landcover, and obstacles surrounding the site of interest. These models rely heavily on the data input into the model, typically meteorological tower data within the computational domain of the proposed site. In the case of this analysis, we used the WIND toolkit data set for 2013 to initialize all these tools, which provides one of the first sources of uncertainty introduced.

As an example, Figure 5 compares one of the input wind data sets, WTK01, with the measured data at the NREL M2 site. We used 24 sectors for plotting the wind rose, centered on a 15° sector. Here, the mid-points of the sectors align with the cardinal directions. The M2 site is about 0.62 km at a heading of 42.92° of WTK01. Hence, this is not a direct comparison; instead, we are comparing wind at two neighboring locations. Nonetheless, this example shows the strength and weakness of initializing the microscale model with modeled data—in this case, the WTK data set. WTK01 data suggest that stronger wind blows from the west, whereas measured data from the nearby M2 site indicates that it is a sector north of west.

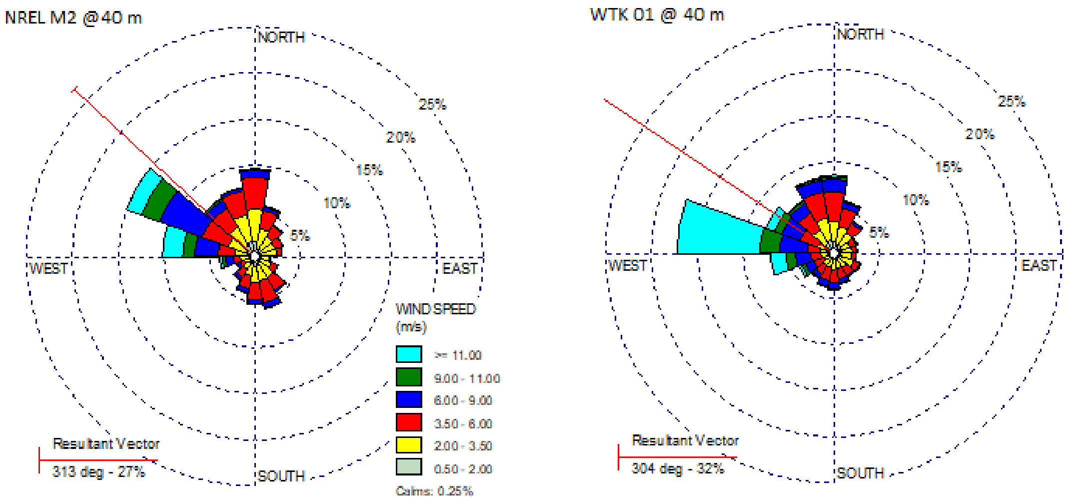

Figure 5. Wind rose at measured M2 and WKT01.

The baseline WIND Toolkit data set estimates the predominant wind direction reasonably well. However, it appears to miss the wind direction by a sector (about 15°) in absolute terms. The annual average wind speed is about 25% higher than the measured value at the M2 site. However, the resultant unit vector of wind direction between these time series differs by just 9 degrees: 313° for measured data and 304° for the WTK01 time series. The magnitude of the resultant vector, which represents the mean resultant vector length, along resultant wind directions are 27% and 32%, respectively. The WIND Toolkit data set for the Hanford site seems to align better with an hourly time series of wind speed, as discussed in greater detail in section 7.2.

7. Results and discussions

Here, we present results for two sites: NREL's M2 site in Colorado and the Hanford site in Washington. We compare standard energy-assessment metrics, such as annual average wind speed, gross energy production, net energy, and capacity factor. For time-series data, we also compare R^2 and FIT for an averaging period ranging over an hour, day, and month.

7.1. NREL M2 Site

Table 1 summarizes these energy-assessment metrics for the NREL M2 site. The blank cell in Table 1 implies that the tool does not provide the metric. OpenWind and WindNinja are the tools that provide time series of wind speed and energy capture at the target location. Hence, we have computed R^2 as well as the FIT for those tools and compared them with the measured data at the M2 site.

Table 1. Energy-assessment metrics at the NREL M2 site.

	Model Class →		Input: WTK01	Mass Conservation	Reduced Order	RANS – CFD	Measurement
SN	Parameters | Example Code		WIND Toolkit Time series	Openwind Time series	Continuum	WindNinja Time series	Real Data (M2)
1	Annual Wind Speed (m/s)		5.55	5.71	5.48	5.55	4.45
2	Gross Energy (MWh)		207.5	213.45	254	207.85	156.32
3	Net Annual Energy (MWh)		179.75	184.92	219.6	180.06	135.43
4	Capacity Factor (%)		20.51	21.09	26.31	20.56	17.84
5	R2: Monthly | Daily		0.831 | 0.560	0.828 | 0.557	-	0.833 | 0.556	1
6	FIT: Goodness of Fit	Hourly	-44.34%	-49.96%	-	-42.77%	100%
		Daily	-1.78%	-10.17%	-	-9.48%	100%

All these tools overestimate annual average wind speed at the M2 site, with overestimation ranging from 23% to 28% relative to the measurement data. Note, however, that the WTK01 wind speed is about

24% higher than the measured value at M2. Because of using the WTK01 data set as input for initialization, these tools exhibit a significant error inherent in the design of this study. The design, however, reflects the state-of-the-art of the distributed wind power industry, in general—where modeled data such as the WIND Toolkit would be used as input into other assessment tools.

Figure 6 presents two of the metrics from Table 1 in the form of a column chart. We present here annual averaged wind speed and the capacity factor (%), the most basic metrics for energy assessment at a site.

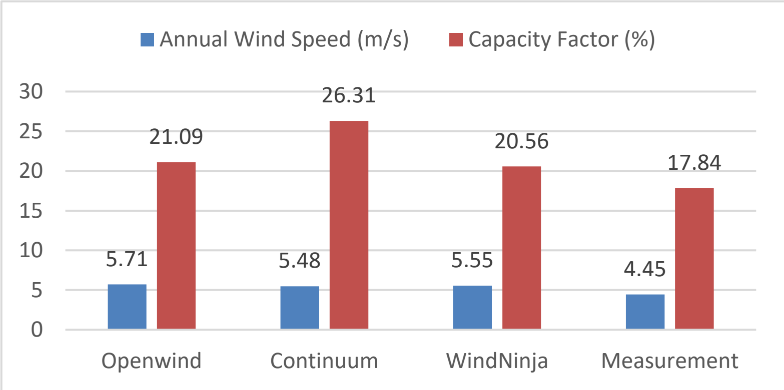

Figure 6. Wind speed and capacity factor at the M2 site.

In converting wind speed to energy production, significant differences are apparent in the results. Openwind estimates the highest and the Continuum the lowest annual wind speed among the tools. In contrast, the net AEP estimated by Openwind is much lower than Continuum. This discrepancy suggests that these tools use different assumptions when converting wind speed to wind energy. Our methodology attempts to maintain a consistent method where applicable. General methods range from the method-of-bin to multiplying the power curve by a simple Weibull distribution, or sectoral Weibull distribution, or time series of wind speed.

In this section, we compare time-series output of tools, where applicable, with the measured data at the site. Two time series may be compared in various ways. A scatterplot is one of the common methods to compare an ordered pair. Here, for practical reasons, we compare the distribution instead of doing a direct point-to-point comparison. Figure 7 presents a count of data in a given wind-speed bin for those hourly time-series data, which included the WIND Toolkit data and measured data at the NREL M2 site.

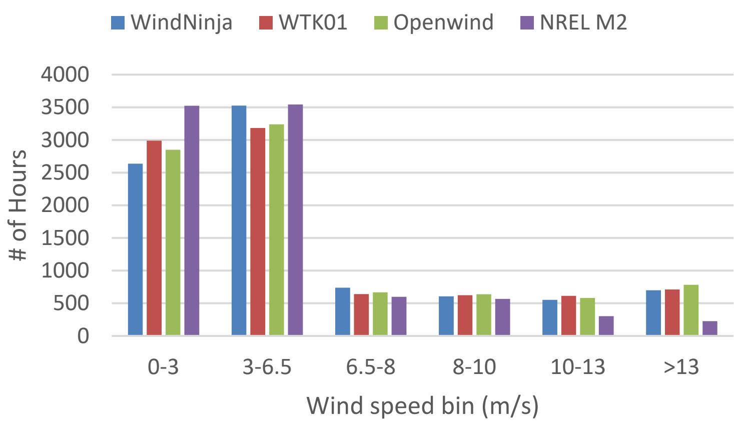

Figure 7. Distribution of wind-speed time series across various bins.

In comparison to the measurement data, discrepancies appear across the entire operation region of the turbine, with more pronounced impacts at assessing the amount of low and higher wind speeds.

Figure 8 compares the wind energy rose at the M2 site computed by Openwind with the same using the measured data. We have binned energy production into six bins of unequal power ranging from 5 kW to more than 75 kW for a nominally rated 100-kW turbine, as presented in the legend.

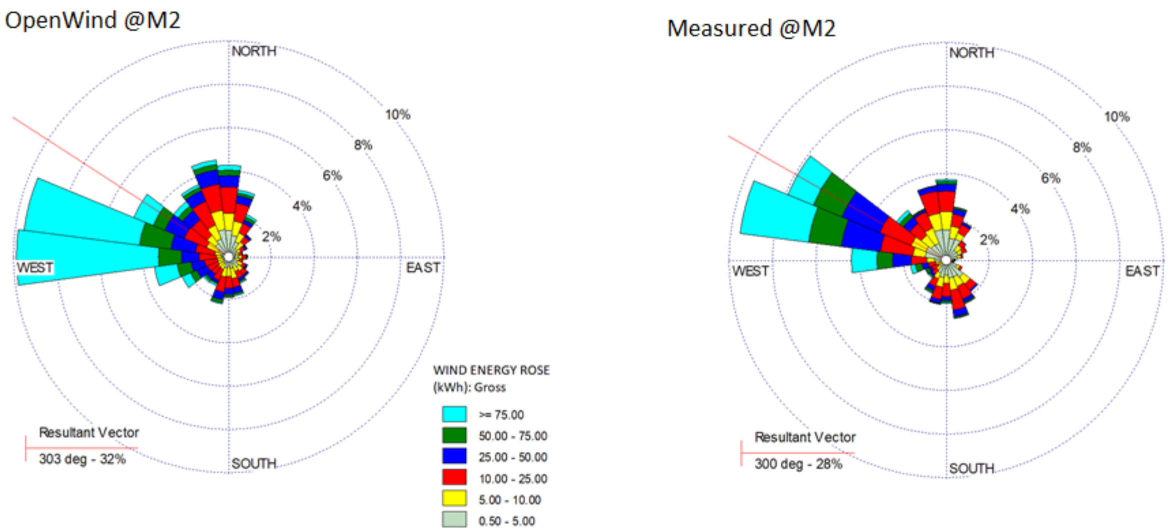

Figure 8. Wind-energy rose at the NREL M2 site computed from Openwind and measured data.

A significant difference exists in energy generated from wind from the west predicted by Openwind to the same computed using the measured data. Openwind estimates that about 7% of the energy in the bin ">= 75kW" would come from the west, whereas it is about 2% for the measured data.

7.2. Hanford Site

The WIND toolkit data set seems to be better aligned with the hourly time series of wind speed measured at the Hanford site. Table 2 presents those same energy-assessment metrics using the assessment tools, WIND toolkit input, and measured data for the Hanford site.

Table 2. Energy-assessment metrics at the Hanford site

	Model Class →	Input: WTK01	Mass Conservation	Reduced Order	RANS – CFD	Measurement
SN	Parameters | Example Code	WIND Toolkit Time series	Openwind Time series	Continuum	WindNinja Time series	Real Data (M2)
1	Annual Wind Speed (m/s)	4.37	4.44	4.49	4.37	3.74
2	Gross Energy (MWh)	146.66	108.76	213	140.46	101.17
3	Net Annual Energy (MWh)	127.05	94.22	184	123.54	87.64
4	Capacity Factor (%)	14.5	10.75	22.07	14.1	10.01
5	R2: Monthly | Daily	0.922 | 0.624	0.918 |0.619	-	0.926 |	1
6	FIT: Goodness of Fit Hourly	-26.66%	-32.18%	-	-22.20%	100%
	Daily	24.27%	21.48%	-	25.52%	100%

The pattern appears identical to that at the NREL M2 site as reflected by the annual averaged wind speed. WindNinja, in this case as well, registers the same wind speed as that of WIND Toolkit data. The time-series statistics, however, are somewhat different, which implies microlevel wind flow that may have been captured differently by the CFD approach.

Figure 9 presents annual averaged wind speed and capacity factor (%) for the Hanford site. Openwind and Continuum seem to make a different assumption and use distinct methods to convert wind speed to energy generation from a wind turbine. Additionally, Continuum appears to overpredict turbine AEP and capacity factor.

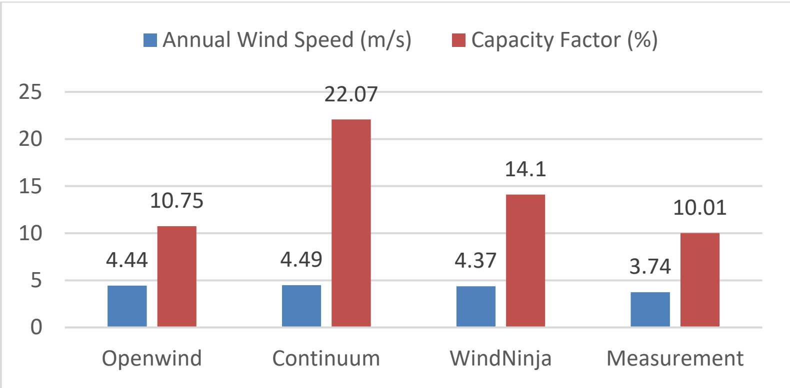

Figure 9. Wind speed and capacity factor at the Hanford site.

All these tools, including the WIND Toolkit data set, underestimate the time (# of hours) that wind speed resides in the 0–3 m/s range. Figure 10 summarizes the number of hours within each wind-speed bin in a year. WindNinja overestimates the count for almost every bin in Region 2 of the power curve.

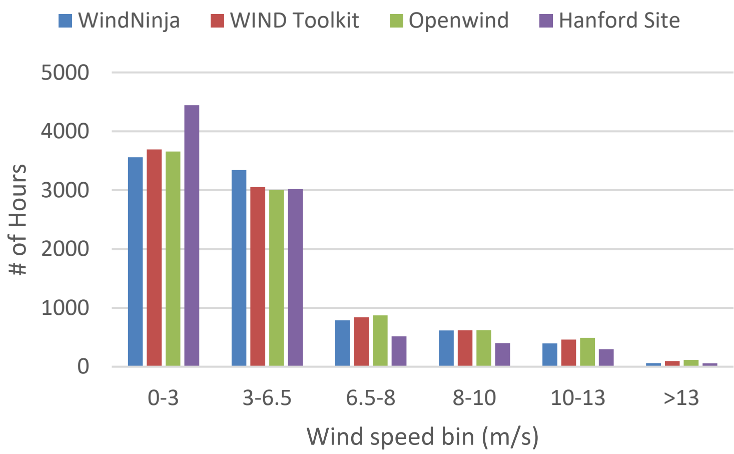

Figure 10. Distribution of wind-speed time series across various bins at the Hanford site.

8. Conclusion

We conducted this study to document a baseline of distributed wind energy-assessment practice. The WIND Toolkit data are not sufficiently accurate to bolster owner confidence of distributed wind project performance at the two sites investigated. Of the tools considered, each provided wind-speed distribution close to that of the wind-speed data used for the model initiation—which is to be expected for relatively open sites as modeled here. Openwind and Continuum appear to make different assumptions and use alternative methods to convert wind speed to energy generation from a wind turbine, with Continuum software consistently overpredicting annual energy production. This issue, raised with the developer of Continuum software, identified a potential error in the power-curve export function that will be addressed in subsequent versions of the software.

Adapting utility-scale tools for the distributed wind industry comes with its own challenges associated with modeling the near-surface layer of the atmospheric boundary layer. The two main sources of the challenges are related to 1) the input data and 2) the uncertainty of low-fidelity models to capture atmospheric physics near the surface of the Earth. Accurate modeling of the wind resource will require agility with both the modeled data set and spatial modeling to capture microscale local effects. A tool that seamlessly integrates these two aspects of standard energy-assessment practice may benefit the distributed wind industry.

This study is not meant to judge the tools being evaluated. Rather, it demonstrates both the modeling options available with tools and their variability to the practitioners of the distributed wind energy industry. Energy assessment involves science but also art—the art of choosing an appropriate tool for a given set of conditions.

9. References

[1] A. Orrell, D. Preziuso, N. Foster, S. Morris, and J. Homer, "2018 Distributed Wind Market Report," Wind Energy Technologies Office, U.S. Department of Energy, 2018.

[2] NREL, "NREL Wind Prospector," [Online]. Available: https://maps.nrel.gov/wind-prospector. [Accessed 8 February 2019].

[3] C. Draxl, A. Clifton, B.-M. Hodge, and J. McCaa, "The wind integration national dataset (WIND) toolkit," *Applied Energy*, **151**, 355–366, 2015.

[4] National Renewable Energy Laboratory (NREL), "Grid Modernization," [Online]. Available: https://www.nrel.gov/grid/eastern-western-wind-data.html. [Accessed 12 July 2019].

[5] NREL, "Wind Integration National Dataset Toolkit," [Online]. Available: https://www.nrel.gov/grid/wind-toolkit.html. [Accessed 3 April 2019].

[6] M. Philippe Beaucage, "Wind Flow Model Performance," AWS Truepower, New York, 2012.

[7] R. Pereira, R. Guedes, and C. S. Santos, "Comparing WAsP and CFD wind resource estimates for the 'regular' user," *Proceedings from EWEC*, 2010.

[8] J. Fields, H. Tinnesand, and I. Baring-Gould, "Distributed wind resource assessment: State of the industry," National Renewable Energy Laboratory (NREL), Golden, CO, 2016.

[9] "NREL National Wind Technology Center (M2)," [Online]. Available: https://midcdmz.nrel.gov/apps/sitehome.pl?site=NWTC. [Accessed 8 January 2019].

[10] "Hanford Meteorological Station," [Online]. Available: https://www.hanford.gov/page.cfm/HMS. [Accessed 12 July 2019].

[11] AWS Truepower, "Openwind User Manual Version 1.8 Rev C," UL AWS Truepower, New York, 2018.

[12] "Continuum Wind Flow Model, Continuum 2.2, User's Manual v1.0," Cancalia Engineering & Consulting LLC, 2016.

[13] FIRE Lab, 3 April 2019. [Online]. Available: https://firelab.org/document/windninja-software.

[14] AWS Truepower, "Openwind: Theoretical Basis and Validation, Version: 1.3," AWS Truepower, Albany, NY, 2010.

[15] N.S. Wagenbrenner, J.M. Forthofer, B.K. Lamb, K.S. Shannon, and B.W. But, "Downscaling surface wind predictions from numerical weather prediction models in complex terrain with WindNinja," *Atmospheric Chemistry and Physics*, **16**, 5229–5241, 2016.

[16] "OpenFOAM," OpenCFD Ltd, [Online]. Available: https://www.openfoam.com/. [Accessed 3 April 2019].

[17] Northern Power Systems, "NPS 100C," [Online]. Available: http://www.northernpower.com/wind-power/nps100/. [Accessed 12 February 2019].

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