Distributed Wind Resource Assessment Using Computational Modelling for Off-Grid, Kilowatt-Size Wind Turbines

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***Abstract*— The ability to accurately perform a distributed wind resource assessment (DWRA) at low cost could be of great benefit to those wishing to install small, kilowatt-sized wind turbines. Since the cost of installing wind measuring equipment can be of the same magnitude as the wind turbine installation itself, such assessments are very seldom done. Computational models hold the promise to provide useful DWRA information at a much lower cost. The purpose of paper is to describe the methods employed and present the results from using wind flow modeling software, in this case Meteodyn WT, to predict wind speeds and Skystream turbine annual energy production (AEP), and compare them to actual data. Results showed errors in predictions of the mean wind speeds were found in the range of 1% to 23%, with very high correlations between the predicted and actual wind speeds regardless of the magnitude of the mean wind speed prediction error. Using more direction intervals in the Meteodyn WT simulation generally led to better predictions. When considering AEP, predictions showed a range of errors from small (<5%) to large (~53%). Distance between the locations of the met tower data and the Skystream turbine, as well as the complexity of the terrain in between, appear to be the important factors causing the difference.**

Keywords - Wind energy, wind resource assessment, computatoinal wind flow modeling, Meteodyn WT, distributed wind energy conversion system, DWECS, DWRA, annual energy production, AEP, wind power prediction

I. Introduction

A major challenge in determining whether to use a distributed wind energy system as part of an off-grid, small-scale renewable energy system is accurately estimating the energy output of the wind turbine. As reported in the 2016 U.S. National Renewable Energy Laboratory report "Distributed Wind Resource Assessment: State of the Industry," accurately predicting the annual energy production (AEP) of a kilowatt-sized wind turbine is a key challenge [1]. The report also listed several research and development challenges and barriers, many related to the minimal data, methodologies, and guidelines available for distributed wind resource assessment (DWRA) validation and benchmarking. Installing wind measuring equipment is usually out of the question for a small turbine installation (< 10 kW), since the measuring equipment can be as expensive as the small wind turbine itself. As an alternative to measuring wind speeds, numerical modeling can be used to predict the wind speeds and AEP, and for a cost much less than installing measurement equipment. However, concerning numerical modeling for DWRA, there is very little in the published literature documenting the methods, results, and accuracy of predicting wind speeds or AEP for small wind turbine applications.

In response to this challenge, in 2017, Northern Arizona University (NAU) performed a study to predict the AEP of a 2.7-kW Skystream 3.7 wind turbine using numerical modeling and publicly available wind speed data. The idea behind this work was to investigate the accuracy with which the output of the Skystream could be predicted, and to document the methods employed and lessons learned. In order to predict the AEP, meteorological (met) tower wind-speed data available in the general vicinity of the Skystream turbine location was used in conjunction with the commercially available software Meteodyn WT (meteodyn.com/en/). The results of this work, some of which will be mentioned later in this paper, are documented in a Master's Thesis [2] and associated journal publication [3]. In that analysis, one year's worth of wind speed data from one met tower was used to predict the AEP of a Skystream for the same year. The work concluded that it is possible to predict the AEP with an acceptable degree of accuracy (<10%), using recommended solver settings for the software. One major benefit of using wind modeling to predict energy output is that it is possible to produce a map of AEP (or capacity factor, or wind power density, or average wind speed, etc.) for a large area in which many potential people can benefit. An example of such a map is shown in Fig. 1 The purpose of the present work is to build upon work reported in the literature [4,5,6] and expand upon the work in the previous study geographically (larger domain), in terms of the number of data sources considered, and in predicting wind speeds as well as AEP.

II. Methods

A. Meteodyn WT

There are several computational flow modeling tools customized for wind energy, Meteodyn WT, WAsP

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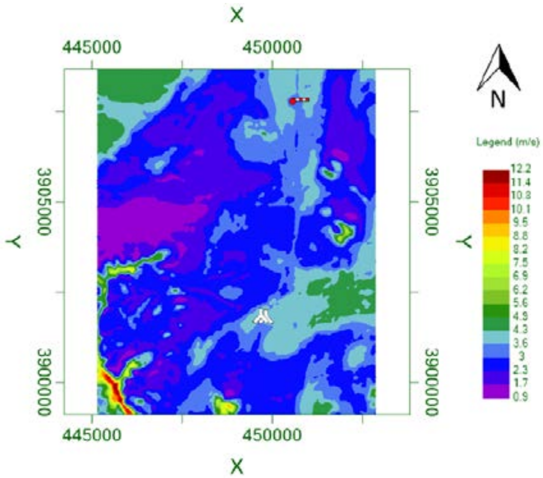

Figure 1 – Example map of AEP showing the predicted output of a 2.7-kW Skystream turbine with a 10-m hub height [3].

(www.wasp.dk), and WindSim (windsim.com) to name a few. NAU has a software license and experience using Meteodyn WT, version 5.0.2, so as a representative computational model, it was selected for use.

Meteodyn WT solves the Reynolds-Averaged Navier-Stokes (RANS) equations written for steady, turbulent, incompressible, and isothermal flow. The equations are solved numerically on a finite-volume mesh set up over the terrain of interest. Turbulence is represented with a Reynolds stress tensor model evaluated using a one-equation closure model for the transport of turbulent kinetic energy [7,8,9]. The mesh employed in Meteodyn WT is rectangular in nature, with the equations discretized on a structured, Cartesian, finite volume grid. The mesh is refined at points of interest using an inflation technique. These points of interest are known as "refinement points" and are used to represent locations of turbines or met towers (see Fig. 2).

Boundary conditions must be specified to integrate and solve the RANS equations. A symmetry boundary condition is applied along the lateral boundaries of the modeling domain, whereas the upper and outlet boundaries assume a homogeneous pressure outflow condition. The ground boundary condition employs Monin-Obukhov theory and the log-law to generate a sink term in the momentum equations in the lower cells of the domain [10,11]. In using Meteodyn WT, the ground boundary conditions are implemented using a digital elevation map to define the topography, surface roughness data, and selection of a forest density classification. The shape of the atmospheric boundary layer and thus wind speed velocity profile at the inlet to the domain is defined by the thermal stability class. The work by Martindale et al. [2,3] explored the effects of forest density, thermal stability class, and roughness data and found that using the recommended solver settings of normal forest density and a neutral thermal stability, combined with 10-m resolution topography data and roughness data from the U.S. National Land Surface Database produced good results. Since the current study is in the same region as Martindale's, the recommended solver settings were used (neutral stability class 2, normal forest density).

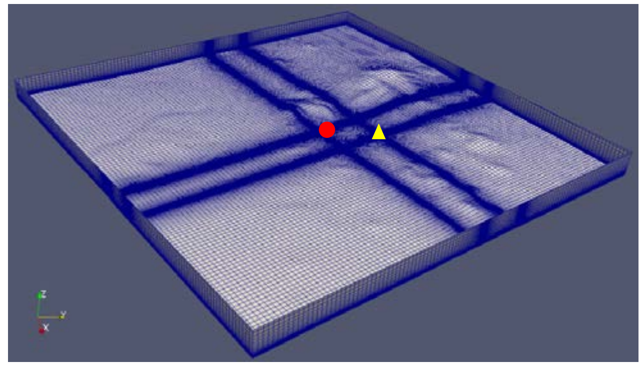

Figure 2 – Image of a mesh with two refinement points represented by the circle and triangle [3].

The RANS equations solved in Meteodyn WT are non-dimensional, resulting in non-dimensional "speed-up ratios" instead of directly computing wind speeds. Calculating speed-up ratios is common in practice, and implemented in both linear and nonlinear computational flow solvers [12,13]. Due to the non-dimensional nature of the solver, after the RANS equations are solved during a simulation, wind speed data from at least one location within the modeling domain is required in order to convert the speed-up ratios into dimensional wind speed results. Because the wind direction is important in calculating the wind speed, due to the effects of the terrain, surface roughness and forest density, Meteodyn WT solves the RANS equations several times, for a range of possible wind directions covering 360 degrees. When running the software, the user defines the range of wind directions to be considered. For example, one can specify the simulation be run for incoming wind from four directions: 0° (from the north), 90° (from the east), 180° (from the south), 270° (from the west), thus a direction interval of 90°. For the present work, the effect of direction interval on prediction accuracy was investigated by using direction intervals of 40° (9 intervals) and 20° (18 intervals). Later, after the "directional" computations are completed, the actual wind directions are accounted for when introducing the wind speed data and dimensionalizing. The reason the direction interval is important to consider is because simulation times can be long when running the software on a high-end workstation (on the order of a day to weeks), and doubling the number of direction intervals nominally doubles the simulation time. The results presented in this paper include a simulation with a 20° direction interval, and a 102-km long geographic domain with 15 refinement points. For these conditions, the simulation run time was 16 days on a Dell Precision T5810 workstation with 64 GB Ram, and using a single Intel Xeon 2.20 GHz processor (though the CPU has 10 cores, NAU's Metoedyn license is only for use on a single processor).

B. *Data Sources*

The ultimate goal of this work was to use wind speed data collected at one location to predict the wind speed and/or power production of a Skystream 3.7 turbine at a different location, and to assess the accuracy of those predictions. To accomplish this, a number of data sources within the modeling domain were employed. Fig. 3 shows an elevation map of the modeling domain, based upon a USGS 10-m resolution national map of

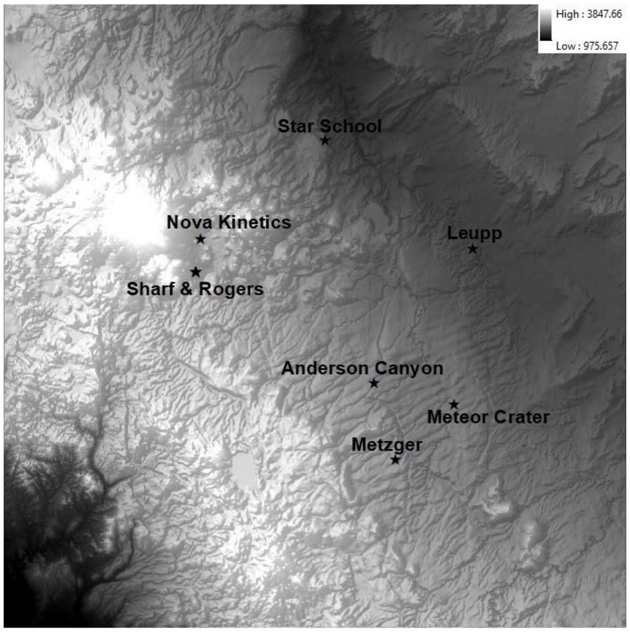

Figure 3 – ArcMap image of the modeling domain, showing location of the met tower or turbine locations (10-m resolution map data from the U.S. Geological Survey [11,12]).

the U.S. [14,15]. This data underlying this map was used to define the topography in the simulation. In this figure, the shading indicates to elevation in meters, and the length of one side of the domain shown is just over 100-km. The locations of the wind speed and Skystream data sources are identified in the figure by name with their locations marked by stars. At some of these locations are met towers, and at some locations are Skystream turbines, as indicated in Table 1. Each location represents a refinement point in the computational mesh. Met towers were outfitted with calibrated NRG #40 wind speed anemometers and #200P wind vanes, collecting data every second and storing 10-minute averaged data. The Skystream 3.7 turbines are rated at 2.4 kW, and were mounted atop either 10-m or 21.3-m tilt-up towers as indicated in Table 1. Daily energy production was recorded for the wind turbines. Because the distance between data sources is of relevance in this work, Table 2 shows the straight-line distance between the met towers and turbines.

C. Simulation and Synthesis

The steps followed in order to perform a Meteodyn WT simulation were as follows:

1. Import 10-meter digital elevation maps for the State of Arizona from the USGS national map (viewer.nationalmap.gov/advanced-viewer/) [14,15].
2. Import the individual elevation maps into the Geographic Information System software ArcMap and stitch together the maps using the mosaic tool (http://desktop.arcgis.com/en/arcmap/).
3. Once a full map of Arizona was created, the clipping tool was used to cut out the portion of the state that was analyzed in this study.

Table 1 – Description of data sources: shaded rows are meteorological towers and unshaded cells are Skystream turbines.

Location	Description of Data Source
Anderson	Met tower with measurements at 30-m and 10-m; 10-min ave.
Metz	Met tower with measurements at 30-m and 10-m; 10-min ave.
Meteor	Met tower with measurements at 30-m and 9-m; 10-min ave.
Nova	Met tower with measurements at 30-m and 20-m; 10-min ave.
Sharf	2.4 kW Skystram 3.7 turbine; 10-m hub height; hourly energy
Rogers	2.4 kW Skystram 3.7 turbine; 10-m hub height; hourly energy
Leupp	Three 2.4 kW Skystram 3.7 turbine; 21.3-m hub; hourly energy

Table 2 – Relative distance between data sources in the modeling domain.

	Anderson (km)	Metz (km)	Meteor (km)	Nova (km)	Sharf (km)	Rogers (km)	Leupp (km)
Anderson	-	14.1	14.7	40.3	37.5	37.6	29.7
Metz	14.1	-	14.4	52.6	48.8	48.9	40.1
Meteor	14.7	14.4	-	54.1	51.8	51.9	28.0
Nova	40.3	52.6	54.1	-	6.0	6.0	48.6
Sharf	37.5	48.8	51.8	6.0	-	0.14	49.6
Rogers	37.6	48.9	51.9	6.0	0.14	-	49.7
Leupp	29.7	40.1	28.0	48.6	49.6	49.7	-

4. Export the elevation map as a .tiff file and import into Meteodyn WT.
5. Obtain U.S. National Land Cover Database (NLCD) 30-m resolution roughness data from the Multi-Resolution Land Characteristics Consortium (/www.mrlc.gov/) [16,17].
6. Roughness data was imported into ArcMap and clipped to the size of the modeling domain. The roughness map for the simulation domain is shown in Fig. 4.
7. Export the roughness information as a .tiff file and import into Meteodyn WT.

Coordinates in these datafiles were represented using the NAD 1983 system, and the points of interest (refinement points) were defined in this coordinate system as well. Once all points

$$\% \, Error = \left| \frac{Predicted - Actual}{Actual} \right| \tag{1}$$

of interest were defined in Meteodyn WT, the direction interval was selected (20°) along with the thermal stability class (2 – neutral) and forest density (normal), and the model was ready for simulation.

After a simulation is complete, non-dimensional speed-up ratios have been computed for each flow direction considered as part of the simulation. Fig.5 shows a map of speed-up ratios for the modeling domain for a flow direction from 240° (West-Southwest). This happens to be the predominant flow direction in the region. The next step in the modeling process is the “synthesis” process. In the synthesis process, wind speed data can be imported to dimensionalize the speed-up ratios, and make predictions of the wind speed and/or power production at any of the refinement points. Once a simulation is complete, numerous synthesis calculations can be performed all relying on the output

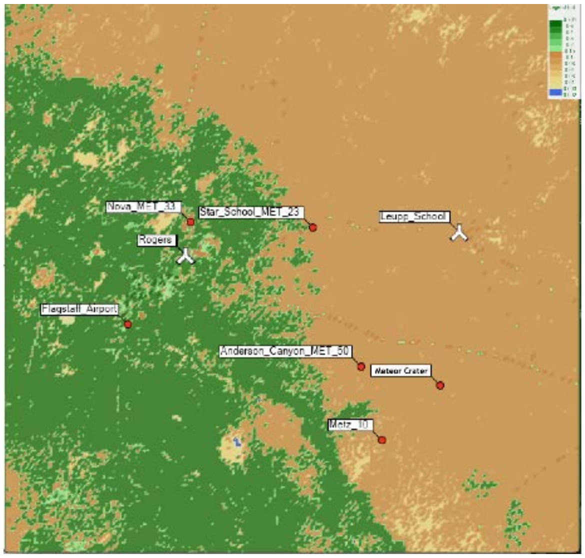

Figure 4 – Surface roughness values across the modeling domain derived from the U.S. National Landcover 30-m resolution Database [13,14].

from the simulation. Synthesis analyses in Meteodyn WT are fairly quick to perform.

D. Test Cases

Two types of synthesis analyses were undertaken: 1) use 10-minute averaged wind speed data from one met tower to make predictions of the 10-minute wind speed at a different met tower location, and then compare the prediction with the actual 10-minute met-tower data; and, 2) use 10-minute wind speed data from a met tower to predict the energy output of a Skystream 3.7 turbine at a different location. In order to compare predictions to actuals, time-coincident wind speed and Skystream energy production data is required. NAU has data at all of the locations shown in Fig. 3. Table 3 shows lists the locations from which met tower data was available for import into Meteodyn WT, and the associated locations where predictions were made. For example, the second row of the table shows that source data from the Anderson met tower wind speed measurement at 10-m above the ground was used to predict the wind speed at the location of the Metz met tower at heights of 10-m and 30-m above the

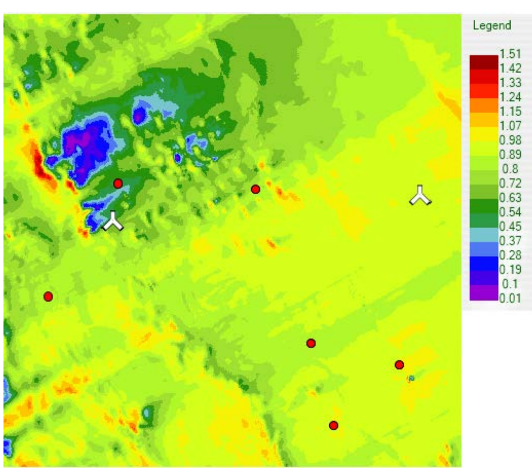

Figure 5 – Map of speed-up ratios computed by Meteodyn WT for the 240° flow direction.

Table 3 – Meteodyn WT synthesis cases, showing location of source data and prediction site.

Source Data	Prediction	Distance	Error Range
Anderson at 10-m	**Metz at 10- and 30-m**	14.1 km	10% to 23%
Anderson at 30-m	**Metz at 10- and 30-m**	14.1 km	4% to 17%
Metz at 10-m	**Anderson at 10- and 30-m**	14.1 km	1% to 10%
Metz at 30-m	**Anderson at 10- and 30-m**	14.1 km	10% to 17%
Anderson at 10-m	**Nova at 20-m and 33-m**	40.3 km	7% to 12%
Anderson at 30-m	**Nova at 20-m and 33-m**	40.3 km	0% to 3%
Nova at 20-m	**Anderson at 10-and 30-m**	40.3 km	1% to 5%
Nova at 33-m	**Anderson at 10-and 30-m**	40.3 km	2% to 4%
Nova at 20-m	**Sharf & Rogers**	6 km	3% to 7%
Nova at 20-m	**Leupp**	48.6 km	53%
Meteor at 9-m	**Leupp**	28 km	26% to 28%

Table 4 – Actual wind speed and AEP values, and description of data sources.

Location	Mean Wind Speed	Description
Anderson at 10-m	4.57 m/s	3 years of wind speed data; 2006-2008
Anderson at 30-m	5.34 m/s	3 years of wind speed data; 2006-2008
Metz at 10-m	5.05 m/s	3 years of wind speed data; 2006-2008
Metz at 30-m	5.65 m/s	3 years of wind speed data; 2006-2008
Nova at 20-m	3.05 m/s	2-mo. wind speed data: Aug-July 2013
Nova at 33-m	3.54 m/s	2-mo. wind speed data: Aug-July 2014
Location	**AEP**	**Description**
Sharf	2.895 MWh	1 year production
Rogers	2.942 MWh	1 year production
Leupp	2.537 MWh	4-year average production

ground. The "Distance" column states the straight-line distance between the two locations, which is 14.1 km between the met towers at Anderson and Metzger. In the rightmost column is listed the "Error Range", which summarizes the range of prediction errors found; these will be presented in the next section, and are summarized here for convenience. The first eight rows are shaded blue indicating that these predictions were of the wind speed at a met tower location. The last four rows are not shaded, indicating that the output of a Skystream turbine was predicted.

While many comparisons could be made between the actual data and predicted, the results to be presented will focus on the annual mean wind speed and the Skystream AEP. For reference, the actual averages of wind speed or AEP are shown in Table 4, including a description of the duration of the data sets.

III. Results

A. Wind Speed Predictions

Fig. 6 shows the results of predicting the mean wind speed at the Metz site using 30-m wind speed source data from the Anderson met tower. The four bars in this bar graph show the absolute value of the errors in the prediction, computed as follows:

Referring to the "Description" column in Table 4 for the "Anderson at 30-m" row, the averages are for three years of data,

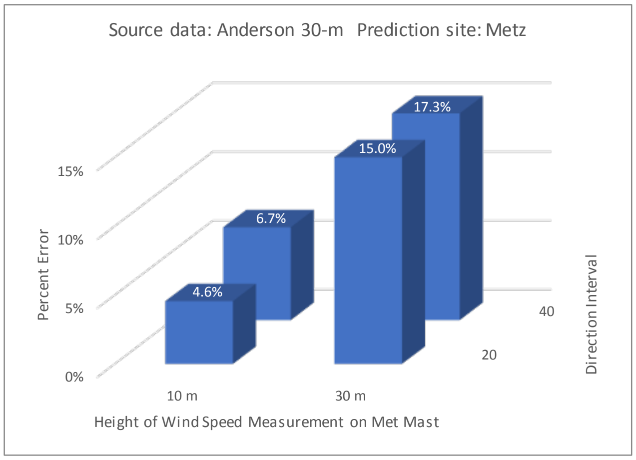

Figure 6 – Errors in predicting the 3-year mean wind speed at the Metz met tower, 10-m and 30-m above the ground, using source data from the Anderson met tower 30-m measurement height.

from 2006 to 2008. For each wind speed measurement height shown on the horizontal axis (10-m and 30-m), there are two bars: one in the foreground and one in the background. The bars in the foreground represent the errors when using a 20° direction interval in the simulation, and the bars in the background correspond to a 40° direction interval. Recall that Meteodyn WT performs directional computations during its simulation. For the direction interval of 20° there were 18 directional calculations in the Meteodyn WT simulation, providing more resolution in the wind speed-up ratios compared to the 40° direction interval where there were nine directional calculations. All bars in the plot are shaded blue indicating that the errors are positive (the prediction is more than the actual). Red bars (as in Fig. 7) indicate negative errors where the predicted is less than the actual. Fig. 6 shows that the predications have lower error at the 10-m height (4.6% to 6.7%), and higher errors at 30-m (15% to 17%). The prediction error is slightly lower when using the 20° direction interval. Using the Anderson 10-m source data to predict at Metz produces similar trends, though the errors are higher, varying from 10% to 24%. For convenience, the range of errors for each comparison are shown in the "Error Range" column in Table 3.

Fig. 7 shows the prediction errors if using Metz 10-m as the source data to predict the mean wind speeds at Anderson. Note the symmetry in these predictions as compared to Fig. 6: the errors are opposite in sign, and the 10-m Metz data has its best predictions for the 30-m height at Anderson just as the 30-m source data at Anderson did its best predictions for the 10-m height at Metz. In both figures, the errors are less when using the 20° direction interval. Considering the full range of errors observed when making predictions between these two sites, the absolute value of the errors were between 1% and 23%.

Another way to evaluate how well the data predictions compare to the actual data is to compute correlation coefficients. In every case tested, the correlation coefficients were above 0.99, indicating a very strong correlation. Figs. 8 and 9 are two plots that demonstrate the strong correlation between the measured and predicted wind speeds. In Fig. 8 is plotted the actual and predicted monthly average wind speeds at the 30-m height at Anderson, using 2006 source data from the Metz 30-m measurements. The two lines, though off in magnitude, are very well correlated. A similar conclusion can be drawn from the plots of the actual and predicted diurnal wind speed profiles for this same data, as shown in Fig. 9.

Figs. 10 and 11 show two more bar charts of wind speed prediction errors, but this time comparing the actual and predicted data between the Nova and Anderson met towers. These met towers had 2-months of time-coincident data. Looking at these figures, it is evident that the wind speed errors are somewhat lower when compared to the previously presented predictions. These errors, being near less than 4%, still show consistent trends in terms of their magnitudes, though the direction interval seems less important. Also, whereas the Anderson and Metz towers were separated by 14 km, the Nova and Anderson towers are 40 km apart. In this case, despite this increase in distance, the errors do not increase.

B. Predictions of Annual Energy Production

The Rogers and Sharf Skytream turbines are located less than 150 meters apart, and energy production from both was recorded for a year-long period in 2011-12. A year's worth of time coincident data was available from the Nova met tower, located 6 km due north of the turbines. Using the Nova met tower data

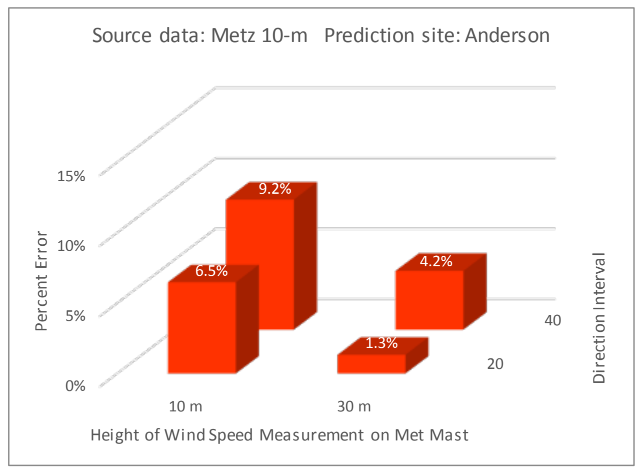

Figure 7 – Errors in predicting the 3-year mean wind speed at the Anderson met tower using source data from the Metz met tower 10-m measurement height.

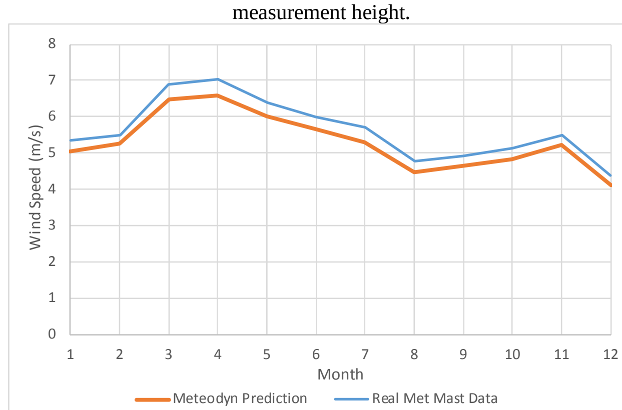

Figure 8 – Monthly average wind speeds for the actual (blue line) and predicted (orange line) 30-m mean wind speeds at Anderson, using Metz 30-m source data from 2006, 20° direction intervals.

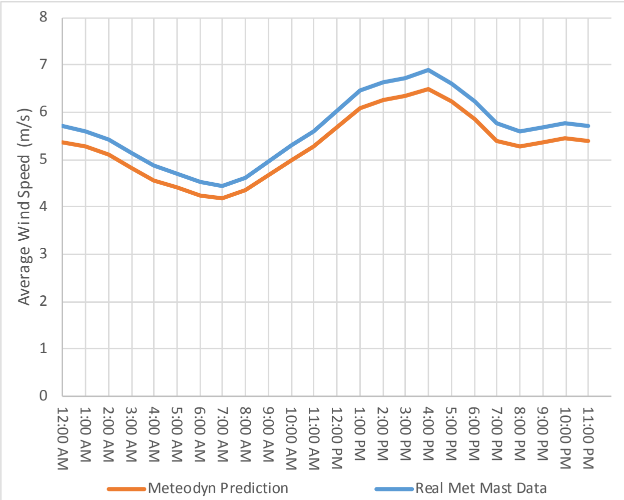

Figure 9 – Diurnal wind speed plot comparing actual (blue line) and predicted (orange line) annual mean wind speeds at Anderson 30-m using 2006 Metz 30-m source data, 20 direction intervals.

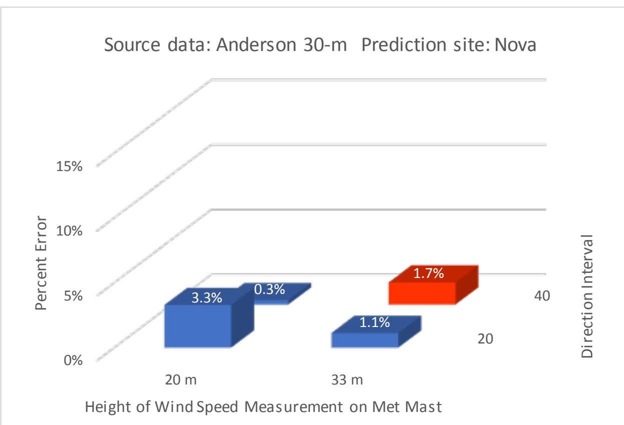

Figure 10 – Errors in predicting the 2-month mean wind speed at the Nova met tower, 20-m and 33-m above the ground, using source data from the Anderson met tower 30-m measurement height.

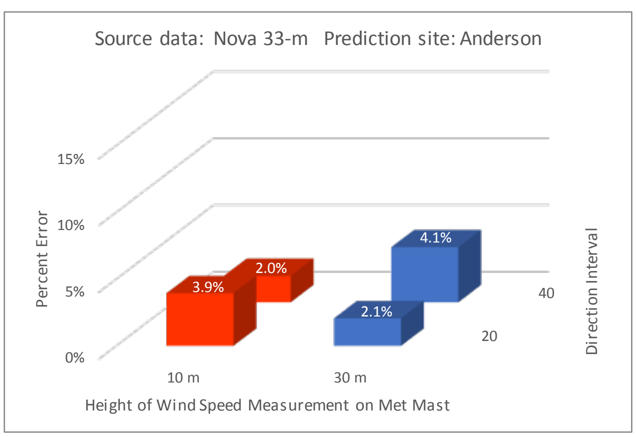

Figure 11 – Errors in predicting the 2-month mean wind speed at the Anderson met tower using source data from the Nova met tower 33-m measurement height.

at 20-m, predictions were made for the AEP of both turbines, and compared to actual AEP. The percent error in these over-predictions are shown in Fig. 12. The errors are modest (between 2.7% and 7.2%), indicating a good estimation, and better for the predictions done with the 20° direction interval.

In addition to evaluating the accuracy of the prediction in AEP, it is also worthwhile to see how well the daily energy production estimates correlate with the actual energy production. Fig. 13 shows the monthly energy production prediction and the actual production for the Sharf turbine. As with the wind speed predictions, the correlation between the energy predictions and actual energy production is very good. With a relatively short distance between the met tower and turbines, and not much change in topography in between, Meteodyn WT makes an accurate prediction.

Two more AEP predictions were made, and are presented in Fig. 14. Data from the Nova met tower at 20-m (left side of figure) and the Meteor Crater tower at 9-m (right side of figure) were each used to predict the average AEP of the Leupp Skystream turbines. The results show much larger over-prediction errors than for the Rogers and Sharf turbines, here ranging from 26% to 53%. The prediction using the Meteor Crater met tower data was substantially better than the Nova met tower data. There are a few potential explanations for this: 1) Nova is further away from Leupp at 48.6 km compared to 28 km for Meteor; 2) The elevation difference between Nova and Leupp is 550 m, whereas it is only 300 m between Leupp and Meteor Crater; and, 3) As confirmed by looking at the topography in Fig. 3, and the roughness map in Fig. 4, there are more substantial changes in both between Nova and Leupp versus Meteor Crater and Leupp.

IV. Conclusions

The purpose of this work was to use met tower wind speed data and wind flow modeling software (Meteodyn WT) to predict wind speeds and Skystream turbine AEP, and compare them to actual data. Best practices were used in applying the modeling software, as documented in this paper. Errors in predictions of the mean wind speeds were found to be in the range of 1% to 23%, with very high correlations between the predicted and actual wind speeds regardless of the magnitude of the mean wind speed prediction error. Using more direction intervals in the Meteodyn WT simulation generally led to better predictions. When considering AEP, predictions showed a range of errors from small (<5%) to large (~53%). Distance between the locations of the met tower data and the Skystream turbine, as well as the complexity of the terrain in between, appears to be the important factors causing the difference. Overall, Meteodyn WT, and likely other wind flow modeling tools, show promise for use in distributed wind resource assessment, but more experience in their application plus more published case studies are needed.

Acknowledgment

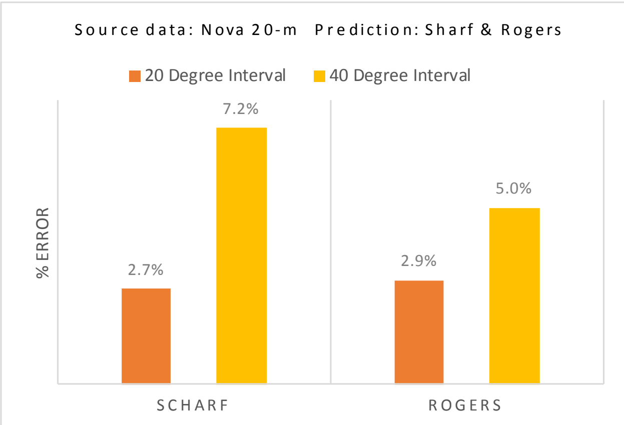

Figure 12 – Errors in predicting the AEP at the Sharf and Rogers Skystream turbines, using Nova 20-m source data.

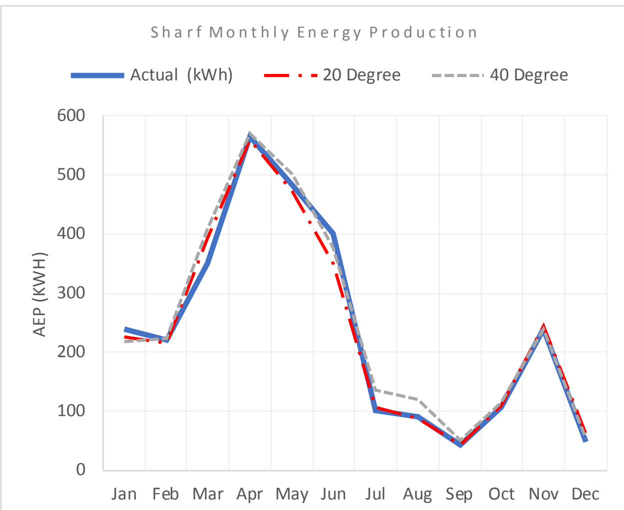

Figure 13 – Predicted and actual monthly energy production for the Sharf Skystream turbine, using Nova 20-m source data.

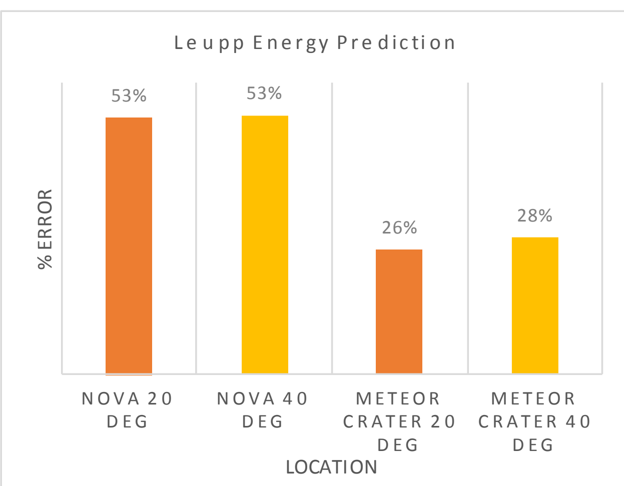

Figure 14 – Errors in predicting the AEP for the Skystream turbines at Leupp, using Nova 20-m source data and Meteor 9-m source data.

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