Distributed Wind Resource Assessment for Small, Kilowatt-Sized Wind Turbines using Computational Flow Modeling Software

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Abstract. A major challenge in deciding to invest in a wind energy system as part of an off-grid, small-scale renewable energy system is accurately estimating the annual energy production (AEP). Computational models hold promise to provide useful distributed wind resource assessment information at a reasonable cost. This paper describes the methods employed and results obtained from using wind flow modeling software, in this case Meteodyn WT, combined with wind speed data to predict the AEP of a 2.4 kW Skystream 3.7 wind turbine, and compare the AEP to measurements. Results showed AEP prediction errors ranging from <5% to ~80% depending on the nature of the wind speed data used. Using a single wind speed data source could lead to an acceptable AEP (<10% error), but could well lead to much higher errors. Two methods of addressing this problem were demonstrated: 1) average several AEP predictions made using single wind speed data sources; or, 2) use multiple data sources simultaneously when making an AEP prediction. The latter of these two appears the most promising with lower errors in AEP. Another significant result of this work was demonstrating that using NREL Wind Toolkit wind speed data can produce good results in predicting AEP.

1. Introduction

When deciding whether to invest in a distributed wind energy conversion system (DWECS) as part of an off-grid, small-scale renewable energy system, a challenge encountered is accurately estimating the energy output of the wind turbine. The 2016 U.S. National Renewable Energy Laboratory (NREL) report “Distributed Wind Resource Assessment: State of the Industry,” stated that accurately predicting the annual energy production (AEP) of a kilowatt-sized wind turbine is a key challenge facing the industry [1]. The report went on to list several research and development challenges and barriers, many of which were related to minimal data, methodologies, and guidelines available for distributed wind resource assessment (DWRA) validation and benchmarking. Installing wind measuring equipment to assess the wind resource is usually not a viable alternative for small turbine installations (< 10 kW), since the measuring equipment can be as expensive as the small wind turbine itself. An alternative to measuring wind speeds is to use computational modeling of wind speeds to predict the AEP. However, the published literature documenting the methods, results, and accuracy of predicting wind speeds or
AEP for small wind turbine applications is quite limited. In 2019, NREL published a framework for conducting DWRA, describing functional requirements and performance metrics, and again identifying the need to validate existing models to understand their appropriate uses and limitations [2].

In 2017, Northern Arizona University (NAU) performed a study to predict the AEP of a 2.4-kW Skystream 3.7 wind turbine using computational modeling and publicly available wind speed data. The purpose of that 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). As will be described later, Meteodyn WT requires some wind speed data in order to “dimensionalize” the non-dimensional output of its simulation. One year’s worth of 10-minute-averaged wind speed data from a met tower was used to predict the AEP of a Skystream turbine for the same year. The work concluded that it was possible to predict the AEP with a reasonable degree of accuracy (<10%) using recommended solver settings for the software [3,4]. For accurate wind simulations such as this, a major benefit of using wind modeling 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 people can benefit. Such a map can be used by people living in that area to estimate their AEP, providing an estimate for use in evaluating the economics of a proposed wind turbine investment. Refer to references [3], [4], and [5] for example AEP maps.

The initial DWRA modeling work conducted at NAU focused on testing Meteodyn WT by predicting the AEP of a Skystream turbine installed near Flagstaff, AZ, USA [3,4]. Met tower data collected 6-km north of the Skystream installation at heights of 20-m and 33-m above ground level (AGL) were used in conjunction with the Meteodyn WT simulation to predict AEP. The full range of solver settings were tested in order to understand their impact on simulation results. The prediction of AEP when using recommended solver settings was within about 3% of the actual AEP, and within 10% for many solver settings. The work concluded that for simulations in this area, the best solver settings were to use a neutrally-stable atmosphere, normal forest density, land surface-roughness data from the U.S. National Land Cover Database (NLCD) [6,7], and topography data from the USGS 10-m resolution land surface map [8,9]. This work was expanded recently to include a larger geographical domain (a square domain about 100-km on a side), in which multiple data sources were available to use in making wind speed and AEP predictions [5]. These simulations showed prediction errors in mean wind speeds ranging from 1% to 23%, with very high correlations (> 0.98) between the predicted and actual wind speed data. Wind data sources and prediction locations were located between 14-km and 40-km apart. The results showed that when the Meteodyn WT simulation was setup to compute wind speeds from more possible directions of the wind (i.e. “directional calculations” as will be explained in the methods section), that the predictions were generally better. It was also observed that source data supplied to Meteodyn WT would yield more accurate predictions when the height of the prediction location AGL was similar to the height AGL of the source data. Less accurate predictions in the AEP resulted when the elevation of the source data and the prediction location differed substantially (> 150-m).

The purpose of the present work is to build upon work reported in the literature [10-12] and expand upon the work in the previous studies [3-5] to make predictions AEP for a new turbine location in Leupp, AZ, USA. Previous studies used met tower data to dimensionalize the Meteodyn WT output. However, in this study, two additional sources are considered: 1) simulated wind speed data from the NREL Wind Toolkit [13]; and 2) TMY3 data (TMY = Typical Meteorological Year) [14]. AEP predictions will be made at locations where data has been collected from three Skytream wind turbines that have been installed in the field.

2. Methods

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

2.1. Meteodyn WT
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 setup 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 [15-17]. 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. 1).

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 [18,19]. 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 using a thermal stability class. The work by Martindale et al. [3,4] 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 study region, the recommended solver settings were used (neutral stability class 2, normal forest density).

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 [20,21]. 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 local 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 might 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, nine direction intervals were selected. The intervals were spaced in two ways: a consistent 40° interval (i.e., 40°, 80°, … 360°). An additional simulation was conducted using 10 intervals that are not equally spaced, but rather with more directions clustered near the predominant direction of the met tower wind speed measurements (20°, 60°, 100°, 145°, 190°, 235°, 280°, 325°, 370°, 415°).
220°, 240°, 260°, 300°, 340°). In this second case, several directions clustered between 190° and 260° were selected by inspecting a wind rose created using met tower wind vane data, and noting that the dominant wind direction is from the southwest. Later, after the “directional” computations are completed, the actual wind directions are accounted for when introducing the wind speed data and dimensionalizing the speed-up factors. The reason the direction interval is an important consideration 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. Ultimately, the two methods of setting the direction intervals led to nearly identical AEP predictions, and thus only the results from the clustered method are presented.

The results presented in this paper are for a 70-km square geographic domain, shown by the yellow dashed-line box in Fig. 2, with 15 refinement points at five locations. Note the deep canyon in the upper left-hand corner of the figure is part of the Grand Canyon National Park. For simulation of this domain, the run time was nine 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).

2.2. Data Sources
The ultimate goal of this work was to use wind speed data known at one location to predict the AEP 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. 2 shows an elevation map of the modeling domain, based upon a USGS 10-m resolution national map of the U.S. [8,9]. The data underlying this map was used to define the topography in the simulation. In this figure, the shading indicates the elevation in meters, and the yellow box approximates the 70-km square modeling domain. The locations of the wind speed and Skystream data sources are identified in the figure by name with their locations marked by stars. As indicated in Table 1, at most of these locations are met towers or points where NREL Wind Toolkit data is available. Abbreviations for the location names are listed in the first column. At Leupp (last row of the table), AEP data was recorded for three Skystream wind turbines installed at the Leupp Elementary School as part of the NREL “Wind for Schools” program, and downloaded from the OpenEI Wind for Schools Portal. Each location in Table 1 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 21.3-m towers. Annual energy production was recorded for each of the wind turbines. The distance between data sources is of relevance when interpreting the results, so Table 2 shows the straight-line distance between the refinement points.
2.3. Simulation and Synthesis

The following steps describe how the surface topography and roughness data were imported into Meteodyn WT in preparation for a simulation:

1. Import 10-meter digital elevation maps for the State of Arizona from the USGS national map (viewer.nationalmap.gov/advanced-viewer/) [8,9].

2. Import individual elevation maps into the Geographic Information System software ArcMap and stitch them together using the mosaic tool, 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.

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/) [6,7].

6. Roughness data was imported into ArcMap and clipped to the size of the modeling domain.

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 of interest were defined in Meteodyn WT, the direction intervals or clustered directions were set along with the thermal stability class (2–neutral) and forest density (normal), and the model was ready for simulation.

After a simulation is completed, non-dimensional speed-up ratios have been computed for each flow direction considered as part of the simulation. An example result from a Meteodyn simulation is the map of speed-up ratios shown in Fig. 3 for a modeling domain with a flow direction of 240° (West-Southwest; from the lower-left side of the figure) [5]. This happens to be the predominant flow direction in the region under consideration in this paper. After the simulation is completed for all directional computations, the next step is the “synthesis” process. In the synthesis process, wind speed data is imported to dimensionalize the speed-up ratios, and make predictions of the wind speed and/or power production at the refinement points. Power production is calculated by using the manufacturer power curve combined with the wind-speed information. Once a simulation is complete,
numerous synthesis calculations can be performed all relying on the output from the simulation. Synthesis analyses in Meteodyn WT are fairly quick to perform, on the order of minutes.

2.4. Test Cases
The synthesis analyses undertaken used wind speed data from one or more locations to predict the energy output of a Skystream 3.7 turbine located at Leupp. Note that if the wind speed data imported at one location is 10-min resolution, then 10-min resolution data is output for the prediction location. In making these synthesis predictions, data was imported from either a single source (e.g. a single met tower or NREL Wind Toolkit site); or, data was imported from several sources (i.e., multiple met towers and/or NREL Wind Toolkit sources). This permitted investigating whether or not using multiple data sources leads to greater prediction accuracies. Each data source listed in Table 1 was used to make AEP predictions the Leupp Skystream turbines.

3. Results

3.1. AEP Predictions with Met Mast Data from a Single Site
Table 3 shows the results of predicting the average AEP of the Leupp turbines using wind speed data from the met tower and TMY3 data listed in Table 1 (recall the abbreviations for the source data are given in Table 1). For each of the five predictions shown, data from only the single met mast listed in the first column of each row was used in the Meteodyn synthesis to make the prediction shown in that same row. The prediction errors were computed as follows:

\[
\% \text{ Error} = \left(1 - \frac{\text{Predicted}}{\text{Actual}}\right) \times 100 \quad (1)
\]

The range of errors in AEP prediction using the met tower data range from 7.7% to 79%. Rows are ordered from lowest error to highest, with the two shaded rows having errors less than 10%. Source data for these two sites are the Winslow Airport (WA) TMY3 and the Meteor Crater (MC) met tower at 30-m. The two predictions with large errors shown in the bottom two rows are both from measurements at the Anderson Canyon (AC) met tower. Data from this met tower has been used successfully in making predictions at other locations [5], but does not perform well when making predictions for Leupp. Related to this, three observations can be made by inspecting the information presented in the sixth, seventh, and eight columns. The sixth column shows the difference in elevation between Leupp and each of the sources of met tower data, all of which are higher in elevation than Leupp. Note that the larger the elevation difference, the larger the prediction error. While this is not always the case, the authors have noticed that predictions made from met tower sources closer to the elevation of the prediction site tend to be more accurate. For the AC data, it is also possible that the error in prediction is at least partly due to the different time frame of the data: the AC data was collected in 2006-2008, while the Skytream data is from 2012-2016. However, the mean wind speeds at a nearby airport show that for years 2006-2008, the mean wind speed is similar to the mean for 2012-2016. Column seven shows the difference in height AGL of the source data and the hub height of the Skystream turbines. At both the MC and AC sites, data sources that are closer to the hub height of the turbine yield lower errors. Once again, the authors have noticed this to be generally the case when using met tower data. The eight column shows the distance between the locations of the source data and Leupp. As can be seen, there is no correlation between distance and error. While it is reasonable to expect errors to increase the further away the source data site is from the prediction site, that does not appear to be an influential factor in this analysis.
To improve on the prediction error and potentially washout some of the bias error that is present, one could average the predictions from all of the sites. Computing the average for the five sites in Table 4 gives an error of nearly 33%. If, however, the AC site is ignored, the average error in the AEP is 7.2% when using data only from WA and MC, no improvement over the best two prediction. The difficulty making such a modification and using sites with a lower prediction error is knowing a priori that a prediction from a site is poor (AC in this case), without having the benefit of a known data source at the location of interest for comparison. Thus, developing “rules of thumb,” such as the effect of elevation difference, etc., that provide this type of information is of importance, particularly when no nearby wind data sources exist.

### 3.2. AEP Predictions with NREL Wind Toolkit Data for a Single Site

As demonstrated in the previous section, if wind speed data is available in the general vicinity of the site of interest, it is possible to make accurate predictions of the AEP. Thus, if useful for making accurate AEP predictions, the NREL Wind Toolkit simulation data could be an excellent source of data. Wind Toolkit data is available at over 125,000 locations across the United States, spaced at 2-km intervals, with simulated wind speed and direction data available at a 10m, 40m, 60m, 80m, 100m, 120m, 140m, 160m, 180m, and 200m AGL. With such extensive coverage, the Toolkit could be instrumental for making DWRA predictions in remote, off-grid locations where no nearby met tower data is available.

Table 4 shows AEP predictions and their errors for the nine sources of NREL Wind Toolkit data considered in this analysis. Data was extracted from the NREL database at five locations: the three locations where we have met tower data (MC, WA, AC), at Leupp, and at a nearby water well known as 5T-529. Wind Toolkit data was selected at 10m, 40m, and 100m AGL. As shown in the table, the AEP prediction errors ranged from about -38% to +25%. Two of the predictions, both using Toolkit data from MC, produced errors of less than 5%. The average error for all nine sites was 10%. Looking at the information in columns six through eight show that, for the NREL data used in this analysis, there is no correlation between the error and the difference in elevation, difference in AGL, and distance between the sites. It is interesting to note that the errors produced by using Toolkit data near Leupp at 40m and 100m were about a 25% underprediction. These results show that it is possible to make an accurate prediction at the Leupp site using NREL Wind Toolkit data, which is significant. The challenge, therefore, becomes identifying a consistent method of using Toolkit data that reliably
produces acceptable errors in predicting the AEP (<10%). Averaging the predictions from all the NREL Toolkit wind data sources led to an error of 10%.

In order to compare the accuracy of predictions from all the single-source data sites (met tower and NREL Toolkit), the contents of Tables 3 and 4 have been combined in Table 5, and ranked from lowest error to highest error. Four of the predictions (the shaded rows) each yielded an error of less than 10%. The data sources for these predictions were from the NREL Toolkit, TMY3, and met tower data, respectively; thus, each type of data source was able to produce an acceptable error. Averaging the AEP prediction from all 14 predictions shown in Table 5 gives an error of 5%. The challenge, however, in using any single site is knowing ahead of time which data sources will lead to an accurate prediction (while in absence of comparison data at or near the prediction site,). In this regard, averaging the predictions from several data sources may be a better strategy. Another strategy is to

| Source Data        | Year        | Predicted, Actual, Error (%) | Difference in elevation AGL (m) | Difference in Distance btw sites (km) |
|--------------------|-------------|------------------------------|--------------------------------|--------------------------------------|
| MC at 100m (NREL)  | 2007-2013   | 2.47, 2.54, -2.7             | 223                            | 78.7                                 |
| MC at 40m (NREL)   | 2007-2013   | 2.44, 2.54, -3.8             | 223                            | 18.7                                 |
| WA at 10m (NREL)   | 2007-2013   | 2.14, 2.54, -16              | 101                            | 11.3                                 |
| Leupp at 40m (NREL)| 2007-2014   | 1.99, 2.54, -22              | 0                              | 0.0                                  |
| AC at 10m (NREL)   | 2007-2013   | 3.15, 2.54, 24               | 336                            | 11.3                                 |
| Leupp at 100m (NREL)| 2007-2015  | 1.90, 2.54, -25              | 0                              | 0.0                                  |
| MC at 10m (NREL)   | 2007-2013   | 3.18, 2.54, 25               | 223                            | 11.3                                 |
| WA at 100m (NREL)  | 2007-2013   | 1.66, 2.54, -34              | 101                            | 39.8                                 |
| ST-529 at 40m (NREL)| 2007-2013 | 1.57, 2.54, -38              | 22                             | 18.7                                 |

Average: 2.28, -10.2
input multiple data sources into Meteodyn WT when completing a synthesis, which is the topic of the next section.

3.3. AEP Predictions with Multiple Met Tower and NREL Wind Toolkit Data Sources
When performing synthesis analysis in Meteodyn, it is possible to ingest multiple data sources to use simultaneously in predicting the AEP, in essence through performing a weighted average. Table 6 shows the results of using several different combinations of the NREL Toolkit and met tower data sources to predict the AEP at Leupp. Of the combinations shown, the first six all generated prediction errors of less than 10% (the shaded rows). The combination of sites in the first row included WA 10m TMY3, MC 30m met tower, and NREL Toolkit MC 40m. These were three of the best performing single-site sources, and they produce a low 1.3% error. In the second shaded row is a combination of five NREL Wind Toolkit sites, leading to a low error of -2.6%. The third row shows an error of -5.1% resulting from using two met tower data sources. Proceeding through the rest of the rows in the table there are many combinations of data sources, including data from the worst performing single-source predictions in Table 5. The full range of predictions errors is from -23% to +42%. If all of the various multi-source predictions are averaged, the resulting AEP is 2.52 MWh, only -0.6% error from the actual average AEP of 2.54 MWh. Indeed, the absolute value of prediction errors when using multiple data sources was 16% compared to 26% for predictions using a single data source.

The general conclusion from performing the multiple-source synthesis runs in Meteodyn is that using multiple data sources is better than using only one. Accurate predictions were made using met tower data, NREL Toolkit data, TMY3 data, and many combinations thereof. Averaging the AEP prediction of several multi-source predictions look like a good approach for minimizing the magnitude of the prediction error.

4. Conclusions
The purpose of this work was to test the use of different wind speed data sources combined with wind flow modeling software (Meteodyn WT) to predict the AEP of a 2.4 kW Skystream3.7 wind turbine, and compare the predictions to measured AEP. Errors in predictions ranged from small (<5%) to large (79%). Using 10% as the threshold for an acceptably low AEP prediction error, it was demonstrated that NAU met tower data, TMY3 data, and NREL Wind Toolkit data each were capable of producing low errors. However, some data from these sources but in different locations or heights AGL generated unacceptably large errors, well greater than 10%. The problem here is that, a priori, it is difficult to tell which of the data sources will lead to good predictions. It was demonstrated that averaging the predictions from several sources led to lower errors in AEP. When comparing use of multiple data sources versus a single data source in the Meteodyn synthesis, it was evident that using multiple sources leads to a superior prediction. Furthermore, averaging the predictions from several combinations of multi-source predictions led to the smallest error in AEP (<1%). When considering single-source predictions of AEP using met tower data, errors tended to be smaller when the source data was at a an elevation closer to that of the prediction site, and also slightly better when the source data height AGL was most similar to the prediction site. The same conclusion did not hold when using NREL Wind Toolkit as the single-source data input. A significant finding of this work is that NREL Wind Toolkit data is an appropriate data source capable of producing accurate AEP predictions. The good news here is that when performing a DWRA for a remote location where no nearby sources of met tower data exist, use of the NREL data makes feasible an assessment when using flow modeling software. Overall, Meteodyn WT, and likely other wind flow modeling software, show promise for use in distributed wind resource assessment. More experience in their use via case study applications reported in the literature are needed to develop confidence in these models, and to produce a set of best practices.
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