Abstract

Information from the several available reanalysis datasets are commonly used in energy yield and site assessment studies to account the long-term significance of local measurements. However, this data is seldom available for specific sites being that in such cases, it is accepted that the geographical point of this data is located at a site with the same wind regime as the location of the meteorological station. This is not always true, especially at complex locations. Efforts can, nonetheless, be done to bypass this handicap and create location dependent data series with long term representativeness providing some local data is available.

A statistical downscaling method allowing, with a minimum of a year worth of meteorological observations at a specific site, to downscale information from reanalysis datasets or from mesoscale simulation models to any site under appreciation for wind energy project development purposes is here presented. Ultimately, this exercise results in the expansion of the time significance of the observed data, both in terms of wind speed and direction, up to a level closer to the long-term expected, depending on the used reference data.

The output time series as attained from the downscaling model can then be used to, using conventional tools, generate wind resource maps and estimate the energy yield of a wind farm. The paper will be focused on presenting the methodology and assessing how both wind resource assessment respond to the usage of this data by analyzing several test cases.

Objectives

We hope to improve the long term representativeness of the data commonly used in resource assessment, energy yield and site assessment studies and, therefore, be able to produce increasingly accurate studies, reducing uncertainties and also to create a work methodology that can be widely accepted by the wind energy industry.

Methodology

An approach based on Empirical Orthogonal Functions is here employed to create weather patterns from long-term meteorological data considered as the reference one. A training period for the model is defined based on the observations performed at a specific location. This training period allows to extend the significance of the observed data when compared to the long term expected, which is then used in resource assessment and energy yield calculations.

The original data matrix is then reconstructed the following way:

\[ X = \sum_{j=1}^{p} \tilde{a}_j \tilde{v}_j \]

Using only the eigenvalues of highest values. The later expression becomes \( j = N \ll p \).

After the selection of the eigenvectors and the corresponding expansion coefficients calculated, a linear regression is used between these and the observed data at the station.

\[ y(t) = \hat{b}_0 + \hat{a}_1(t) * b_1 + \ldots + \hat{a}_N(t) * b_N \]

After the transformation coefficients were calculated for the training period these can be used to extend the representativeness of the model data series to the site of the meteorological station.

Results

The method was tested using data from the mesoscale model operated by Meteorigalicia, for different locations spread across northern Portugal, classified as complex terrain, the following tasks being accomplished for each one of them:

- Analysis were performed for the most important statistical parameters between the output series of the downscaling model, the data series from the mesoscale model and the data series observed at each meteorological station;
- Relative mean error maps were constructed showing the error between the wind resource calculated with the observed data series and the output series from the downscaling model;
- Mean error variation maps were calculated, showing the difference in the mean error obtained when the resource is calculated with the direct output of the mesoscale model and when the same is done using the data series outputted by the downscaling model.

Table 1 exhibits the attained results at one of the sites. In this particular case, the use of a statistical downscaling methodology led to significant improvements when in comparison with results attained directly from mesoscale information.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Observed</th>
<th>Mesoscale</th>
<th>Mesoscale-dowscaling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean wind speed [m/s]</td>
<td>7.0</td>
<td>7.8</td>
<td>12.4</td>
</tr>
<tr>
<td>RMSE [m/s]</td>
<td>-</td>
<td>2.925</td>
<td>-</td>
</tr>
<tr>
<td>Weibull - A [m/s]</td>
<td>7.7</td>
<td>8.8</td>
<td>15.6</td>
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<tr>
<td>Weibull - k [-]</td>
<td>1.50</td>
<td>2.06</td>
<td>37.2</td>
</tr>
</tbody>
</table>

Conclusions

Regarding the principal statistical parameters we conclude that the models depends heavily on the location being tested. Giving, for complex location either better or worse results the ones obtained directly by the mesoscale model. However, analyzing the results for the wind resource calculations we see an improvement both in wind speed and power density results. The errors obtained with the downscaling model are consistently lower and the error interval significantly smaller.

References

2. Regional Downscaling of IPCC Sea Surface Wind Predictions Based on Long-term Satellite Data Statistics, 35th Climate Diagnostics and Prediction Workshop Raleigh, NC October 4-7
3. Meteorigalicia - Consellería de Medio Ambiente, Territorio e Infraestruturas, Xunta de Galicia

EWEA 2014, Barcelona, Spain: Europe’s Premier Wind Energy Event