Fusion for Modeling Wake Effects on Wind Turbines

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Abstract – Wind turbine wakes cause power reduction and structural loading. A data-driven approach is proposed for wake modeling to provide the azimuth, angular spread, and intensity of wakes. We introduce three wind speed difference definitions for wake analysis. The wake identification is automated using morphological imaging operators. The wake pattern is complicated by multiple neighboring turbines. Four fusion schemes are proposed to draw a complete picture. A similarity based clustering enhances the final fusion result by treating clusters, each with specific features, equally.

Keywords: Wind Turbine, Wake, Fusion, Image Processing, Automation

1 Introduction

Wind energy is a major source of renewable energy with great potential in the current energy crisis. Monitoring the health of wind turbines is important to maximize production by avoiding downtime and improving efficiency. The turbine’s performance will vary from its optimum behavior for a variety of reasons - wind turbulence, degradation, system faults, or other causes. Although currently sensors expressly targeted for diagnostics and prognostics purposes do not reside in the turbine architecture, we may use any decline or change in a performance metric for such purposes.

A modern wind farm may consist of tens to thousands of turbines, and their co-existence complicates the air dynamics. The farm layout is designed based on terrain and wind maps, which is often non-uniform, especially for offshore applications. What’s more, the placement of turbines may be altered on account of unfavorable terrains or practical reasons. Tony Burton, David Sharpe, Nich Jenkins and Ervin Bossanyi [1] state that “As it extracts energy from the wind, a turbine leaves behind it a wake characterized by reduced wind speeds and increased levels of turbulence”. This phenomenon is not a fault. The power generation returns to normal when the wind changes its direction, and the downwind turbine is no longer in the wake region.

There have been many efforts in modeling the wake but with limitations. Ainslie proposed an eddy viscosity model based on the Navier-Stokes equation of fluid flow [2], which is less capable of predicting turbulence levels in the wake. In a later work, Quarton and Ainslie proposed an empirical formula for added turbulence based on measurements in wind tunnels and far field [3]. An improved expression was proposed by Hassan [4]. Frandsen and Thogersen proposed a model based on the geostrophic drag law, which takes into account the additional surface roughness caused by the turbines themselves [5]. Despite the large amount of work in this area, no consensus has yet emerged on a sufficiently, well-validated formula for turbulence intensity within a wind farm. A recent study on a large, dense wind farms in complex terrain and offshore has compared six models with measurements [6]. The study was a first-hand comparison in a relatively controlled setting, where the turbines were aligned on a grid, and the wind chosen to flow from three specific directions. The applicability of this model has not been successful on arbitrary layout of turbines for wind flowing from all directions.

In this paper, a data-driven approach is proposed to model the patterns in plots of wind speed difference versus wind direction. From the patterns one can identify the intensity and directions the turbine is in wake. We automate this process, to apply the technique to hundreds of turbines on this farm. The objective is to determine a table of the azimuth angles, the angular spreads, and the intensities of the wake effect on the downwind turbines.

The rest of the paper is organized as follows. Section 2 describes several evaluation schemes of wake effects. Section 3 provides an automatic wake analysis technique based on morphological image operators. Section 4 fuses the results from multiple neighboring turbines to derive a unique wake pattern for each turbine of interest on the farm. Section 5 concludes this paper with future work.

2 Wake identification

When a turbine operates in the wake of another turbine, the downwind turbine is subjected to horizontal wind shear, and the blade load fluctuations also increase [1]. Immediately behind a turbine, its wake can be approximated by a region slightly larger in diameter than the turbine with reduced wind speed [7]. The reduction in velocity depends on the thrust coefficient of the turbine, which determines the momentum extracted from the flow. At a further distance, the wake and the surrounding flow start to mix making the
width of the wake increase; however, the velocity deficit in the wake is eroded. The wake becomes broader and less velocity deficient until the flow has fully recovered far downwind. The turbine also generates turbulence by the blades, nacelle and tower, but this turbulence is of relatively high frequency, and decays relatively quickly [8]. Ultimately, wind speed is the major factor in both wakes and power generation, so our wake identification is focused on wind speed difference.

2.1 Data synchronization

In wake analysis, when adjacent turbines are compared data synchronization between multiple turbines is important. The Supervisory Control And Data Acquisition (SCADA) system collects the measurements continuously from all turbines and records the data every 10 minutes, but there are some common problems such as missing data, multiple records with the same time stamps (duplicates), or repeated readings at several continuous time stamps (stuck). Outliers also need to be removed. Turbine orientation needs to be taken into account.

In order to solve these problems, we propose a “common frame” scheme which contains the time stamps of data from all turbines. Status fields are then created for each time stamp on the common frame that indicates whether the associated measurements for each turbine are missing, duplicate or stuck.

2.2 Definitions of wind speed difference

In the following definitions, the wind speeds of the two turbines being compared are denoted by \( w_{s1} \) and \( w_{s2} \).

2.2.1 Direct difference

The first and most straightforward definition is shown in Figure 1 (a). Denote it as \( wsd_1 \), and it is defined by

\[
wsd_1 = w_{s1} - w_{s2}. \tag{1}
\]

In the data between turbines, \( wsd_1 \) shows a range of \([-2, 2]\) if normal, and \([-5, 5]\) if in a wake region.

2.2.2 Ratio difference

Wind speed deduction in the wake region depends on the wind speed. Here the WSD is taken relative to the wind speed of the upstream turbine. This makes the wind speed deduction due to being in the wake region equally apparent at all wind speeds. We define

\[
wsd_2 = \frac{w_{s1}}{w_{s2}} - 1. \tag{2}
\]

The problem of a zero-denominator is avoided by considering only those wind speeds at the upwind turbine greater than 0.05 meters/second. \( wsd_2 \) is shown in Figure 1 (b). \( wsd_2 \) compresses the valleys and stretches the peaks. Due to the nature of this definition, the wake analysis will be focused on the second turbine by identifying the peaks.

The problem of a zero-denominator is avoided by considering measurements for each turbine are missing, duplicate or stuck.

2.2.3 Normalized difference

The third definition, \( wsd_3 \), normalizes the WSD by the average of the two wind speeds to enhance the sensitivity to small wind speeds by

\[
wsd_3 = \frac{w_{s1} - w_{s2}}{(w_{s1} + w_{s2})/2} = 2 - \frac{4}{w_{s1}/w_{s2} + 1}, \tag{3}
\]

where \( w_{s1} > 0, w_{s2} > 0, \) and thus \( x = w_{s1}/w_{s2} \in (0, \infty), \) and \( wsd_3 = 2 - \frac{4}{x+1}, \) which is in the shape of Figure 2, when \( x > 0 \). The theoretical range of \( wsd_3 \) is \([-2, 2]\). The practical data are mostly in the range of \([-1, 1]\) (between the red dotted lines), which, inversely, shows that the wind speed ratio is mostly in the range of \(0.3\) to \(3.2\) (between the green dashed lines). The range of \( wsd_3 \) in data is consistent with \( wsd_2 \) (0.3 to 3.2 minus 1 yields \(-0.7\) to \(2.2\), which is close to \(-1\) to \(2\) in our previous observations of \( wsd_2 \)). The WSD plot by definition \( wsd_3 \) is in Figure 1 (c).

Comparing the three plots in Figure 1, we see that \( wsd_3 \) is suitable for both valley and peak detections, where the wake identification on the first turbine is by finding valleys,
and that on the second turbine is by finding peaks. We limit the range of \( wsd_3 \) to be from \(-1\) to \(1\). \( wsd_3 \) is flexible in both directions, and our analysis hereafter uses Normalized Wind Speed Difference.

### 2.2.4 Special cases of wake effects

When two turbines ("Duplets") are located without other turbines in their neighborhood, their wake angles are \(\alpha\) and \(\alpha+180\). The WSD of a duplet is shown in Figure 3 (a). Multiple turbines in the middle of a chain cluster may not have significant WSD, since they are both in wake regions. An example of a WSD is shown in Figure 3 (b). When several turbines are located in proximity, multiple wakes constitute a compound wake, whose tip may be shifted away from the expected direction derived from map layout, as illustrated in Figure 3 (c). A turbine located deep inside a farm is in the wake region of many turbines around it, causes complicated wake patterns, as in Figure 3 (d).

### 2.3 Cause and effect relation in wakes

#### 2.3.1 From wind speed difference plots

The WSD between two turbines is plotted against the wind direction to examine the wake effect. A WSD plot is shown in Figure 1 with "valleys" and "peaks". A valley indicates that the first turbine has a smaller wind speed at that particular wind direction, and hence it is in the wake region of another turbine.

Some WSD plots do not have valleys or peaks. This does not necessarily mean that there is no wake effect. It is possible that both turbines may be experiencing wakes to a similar intensity. This can happen in a chain as in when the turbines are in the middle of a chain cluster (A chain cluster is a row of turbines aligned nearly on a line). If the wind flows along the direction of the cluster, both turbines are in the same region of wake and hence there is no significant wind speed difference, such as in Figure 3 (b).

#### 2.3.2 From map layout

The wind turbine wake is complicated by the chaos of air dynamics, the moving patterns of the turbine blades, the shapes, heights and locations of the turbines, etc. In a simplified model, the map layout can provide a blocking list which tells us the upwind turbines and their direction. The range of the wake region depends on the height and span of the turbines and the maximum wind speeds the turbines operate under. A commonly used range of wake region is 250 meters. Our data mining indicates that 250 meters range is insufficient to explain all wake effects. We use a 1000 meter range because beyond 1000 meters there are no observable wake effects in the data.

In a WSD plot, Figure 1 (a), the vertical line is the direction turbine \(A\) expects to be the wake of turbine \(B\), which is determined from the map layout. From the plot, turbine \(A\) indeed experiences the wake of turbine \(B\) around the expected direction. There are other wakes in the WSD for turbine \(A\), for which the causes cannot be explained from this plot alone.

#### 2.3.3 Utilization of both data and layout

Wake detection from wind speed difference (\(WSD\)) and from map layout (\(Map\)) may not always be consistent, yielding a truth table in Table 1.

<table>
<thead>
<tr>
<th>(WSD)</th>
<th>(Map)</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>No Wake</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>Low Wind</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Turbine Fault</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>Wake</td>
</tr>
</tbody>
</table>

### 3 Automation of wake analysis

In a WSD plot, a wake effect is suggested by the presence of valleys (or peaks). Their width shows the angular span the turbine is in wake. Their depth shows the intensity of it. There are often tens or hundreds of turbines on the wind farm, and an automated procedure of identification is desirable. Image processing is used to locate the valleys or peaks and measure their widths and depths.

The scatter plot of data points on the WSD plot may be sparse. Two morphological image processing operators, dilation and erosion, are employed to detect the underlying shape. We first utilize dilation to connect the data points, so that the pattern in the data points forms a connected shape. The outliers are then eroded away. Erosion will cause the major shape to diminish as well, so we use dilation again to restore the size of the shape, and trim it again by erosion.
3.1 Description of dilation and erosion
Each image is a matrix of pixel values. The pixel value of a WSD plot is in the set of \( \mathbb{Z} = \{0, 1\} \). Suppose that the full image (a WSD plot) is \( \text{Img}_A \), and the filter of dilation or erosion, often called \textit{structuring element}, is \( \text{Img}_B \). An image is a two-dimensional matrix, or, \( \text{Img}_A \in \mathbb{Z}^2 \), and \( \text{Img}_B \in \mathbb{Z}^2 \).

3.1.1 Dilation
The dilation of \( \text{Img}_A \) by \( \text{Img}_B \), denoted by \( \text{Img}_A \oplus \text{Img}_B \), is defined as [9]

\[
\text{Img}_A \oplus \text{Img}_B = \{ z | (\text{Img}_B)_{z} \cap \text{Img}_A \neq \emptyset \}, \tag{4}
\]
where \( \text{Img}_B \) is a reflection of \( \text{Img}_B \), namely,

\[
\text{\overline{Img}}_B = \text{Img}_B^\sim, \tag{5}
\]
when \( \mathbb{Z} = \{0, 1\} \). The negation operator yields \( 0^\sim = 1 \) and \( 1^\sim = 0 \). \( (A)_z \) is a translation of set \( A \) by point \( z = (z_1, z_2) \), defined as

\[
(A)_z = \{ c | c = a + z, \text{for } a \in A \}. \tag{6}
\]
We have \( A = \text{\overline{Img}}_B \) in our case.

3.1.2 Erosion
The erosion of \( \text{Img}_A \) by \( \text{Img}_B \), denoted by \( \text{Img}_A \ominus \text{Img}_B \), is defined as

\[
\text{Img}_A \ominus \text{Img}_B = \{ z | (\text{Img}_B)_{z} \subseteq \text{Img}_A \}. \tag{7}
\]

The erosion of \( \text{Img}_A \) by \( \text{Img}_B \) can be regarded as the set of all displacements that \( \text{Img}_B \) completely resides in \( \text{Img}_A \).

3.2 Automatic procedure for wake identification
The proposed procedure is as follows.

1. Draw the WSD plot (by \textit{wsd}_3) as black points without map reference. Limit \( x \)-axis from 0 to 360 degrees. Limit \( y \)-axis from \(-1\) to 1. Negate it to have white points on the black background (to save calculation resources) and save it as an image.
2. Set a threshold of wake region WSD, \( d \).
3. Read in the image without the axis frame. Determine the location of zero-line, the \( d \)-line, and the pixel size relative to the original \( x \)-axis and \( y \)-axis.
   If the image size is found out to be \( p \) rows by \( q \) columns, and the WSD plot range is set to be \([0, 360] \) on \( x \)-axis, and \([lr, ur] \) on \( y \)-axis, then a pixel location at \( r \)-th row and \( q \)-th column will be mapped to have value \( r_1/p \cdot (ur - lr) + lr \) at angle \( r_2/q \cdot 360 \).
4. Denote the original WSD plot as \( \text{Img}_{\text{orig}} \). Dilate it by a \( 2 \times 2 \) all-ones filter to get \( \text{Img}_1 \).
5. Erode \( \text{Img}_1 \) by a \( 3 \times 3 \) all-ones filter to get \( \text{Img}_2 \).
6. Dilate \( \text{Img}_2 \) by a \( 20 \times 20 \) all-ones filter to get \( \text{Img}_3 \).
7. Erode \( \text{Img}_3 \) by a \( 5 \times 5 \) all-ones filter to get \( \text{Img}_4 \).
8. Check the WSD shape crossed by the \( d \)-line, record the transition pixels as the starting and ending points of a wake region. Determine the tip of the wake shape.
9. The location of the tip of the wake shape is recorded and transformed back to the WSD plot quantities as the wake direction and intensity. The location of the transition pixels are recorded and transformed back to the WSD plot quantities as the azimuth of the wake.

The four \textit{structuring elements} (filters) used in dilations and erosions are selected based on expert knowledge to retain the wake shape as much as we can, while clearing out all the outliers. Other shapes of the filters, such as diamond, disk, rectangle, or octagon, are also tried but found out to leave frizzes making the task harder, and hence the square filters are used.

An example of a sequence of images generated by this automatic procedure for turbine pair with WSD shown in Figure 1 is shown in Figure 4. The threshold is chosen as \( d = -0.3 \), and three valleys are identified. The identified wake regions are overlaid with the original WSD plot in Figure 4 (g). The numerical results on the azimuth (in degrees) and the intensity (in \textit{wsd}_3 scale) of the wakes are listed in Table 2. The second valley is prominent. The first and third valleys are relatively faint, but still identified. The sensitivity of the valley detection depends on the threshold, \( d \).

Table 2: The numerical results of the identified wakes (location in degrees, intensity in \textit{wsd}_3 scale)

<table>
<thead>
<tr>
<th>Turbine</th>
<th>Valley</th>
<th>Left</th>
<th>Right</th>
<th>Spread</th>
<th>Intensity</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>B</td>
<td>36.91</td>
<td>29.03</td>
<td>7.88</td>
<td>-0.31579</td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td>82.53</td>
<td>62.21</td>
<td>20.32</td>
<td>55.58</td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td>291.15</td>
<td>284.52</td>
<td>6.63</td>
<td>13.27</td>
</tr>
</tbody>
</table>

4 Fusion for deriving the comprehensive wake pattern
The presence of multiple valleys at different wind directions on a single WSD plot suggests that, if the valleys are due to wake, then they may not be caused by only one turbine. A complete understanding of the wake pattern on this central turbine demands an analysis from all of its neighbors.

Turbine A is surrounded by several turbines, as shown in Figure 5, which is an extraction from a much larger wind farm. The data from the unlabeled turbines in Figure 5 are unavailable, and hence they are not included in the analysis later on. All the pair-wise WSD plots are shown in Figure 6 on the last page (the WSD plot between turbine A and turbine B is also in Figure 1).

4.1 Similarity based clustering
Turbine A’s neighbors are clustered based on their physical locations, and their WSD plots show similarity if they
are in the same cluster. For instance, the WSD plots of turbine $A$ with turbines 1 and 2 are similar, and the ones with turbines 3 and 4 appear to show a peak near the right hand side, which implies that turbine $A$ blocks them at those directions. With turbine 5, the right peak moves further towards the right, as turbine 5 is located more towards the right. The WSD plots with turbines 6 to 9 look similar.

Besides human inspection, a quantitative evaluation on the similarity between the WSD plots, $Img_A$ and $Img_B$, is proposed as

$$\text{similarity}(Img_A, Img_B) = \frac{n(Img_A \cap Img_B)}{n(Img_A \cup Img_B)},$$  \hspace{1cm} (8)$$

where $n(A)$ is the element count of set $A$. The numerical results on the similarities of the 12 WSD plots in Figure 6 are reported in Table 4. Based on the histogram analysis of the observed similarity scores in Figure 7, a threshold of 0.78 is chosen to separate the similar/dissimilar WSD plots, and the clusters of the similar WSD plots are formed. A turbine may belong to more than one cluster. Considering the turbine layout in Figure 5 together with the clustering, we discover some interesting patterns, which lead to the fundamental similarity rules indicated in Table 3.

Table 3: Clusters identified by the similarity clustering

<table>
<thead>
<tr>
<th>No.</th>
<th>Members</th>
<th>post result assigned description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cluster 1</td>
<td>{1,2,3,4,5}</td>
<td>Northern cluster</td>
</tr>
<tr>
<td>Cluster 2</td>
<td>{3,8,11}</td>
<td>Middle of a chain cluster</td>
</tr>
<tr>
<td>Cluster 3</td>
<td>{4,9,11}</td>
<td>East end of a chain cluster</td>
</tr>
<tr>
<td>Cluster 4</td>
<td>{5,6}</td>
<td>West end of a chain cluster</td>
</tr>
<tr>
<td>Cluster 5</td>
<td>{7,8,9}</td>
<td>Western cluster</td>
</tr>
</tbody>
</table>

Wake pattern analysis requires integrated efforts in physical modeling, sensor measurements and expert knowledge, etc. Pravia, Prasanth, Arambel, Sidner and Chong proposed a general framework for hard/soft information fusion [10]. Hard information fuses measurements arising from physics-based sources, such as the wind speed measurements, the WSD plots, and the turbine layout map. Soft information is the information from human-based sources, such as the expert knowledge on inspecting the WSD plots, the threshold determination, and the evaluation of the results. The diagram of the hard/soft fusion for wind turbine wake analysis is provided in Figure 8.

After obtaining the WSD between turbine pairs, they are fused to improve identification of wakes. Four fusion schemes are presented below.
Table 4: Similarity between the WSD plots of turbine A versus its neighbors

<table>
<thead>
<tr>
<th>Turbines</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>B</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.00</td>
<td>0.82</td>
<td>0.79</td>
<td>0.78</td>
<td>0.74</td>
<td>0.66</td>
<td>0.68</td>
<td>0.71</td>
<td>0.63</td>
<td>0.66</td>
<td>0.74</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>0.82</td>
<td>1.00</td>
<td>0.82</td>
<td>0.77</td>
<td>0.82</td>
<td>0.73</td>
<td>0.70</td>
<td>0.71</td>
<td>0.61</td>
<td>0.69</td>
<td>0.74</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.79</td>
<td>0.82</td>
<td>1.00</td>
<td>0.84</td>
<td>0.79</td>
<td>0.77</td>
<td>0.74</td>
<td>0.78</td>
<td>0.65</td>
<td>0.68</td>
<td>0.78</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>0.78</td>
<td>0.77</td>
<td>0.84</td>
<td>1.00</td>
<td>0.74</td>
<td>0.76</td>
<td>0.71</td>
<td>0.75</td>
<td>0.64</td>
<td>0.63</td>
<td>0.78</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>0.78</td>
<td>0.82</td>
<td>0.79</td>
<td>0.74</td>
<td>1.00</td>
<td>0.79</td>
<td>0.72</td>
<td>0.74</td>
<td>0.73</td>
<td>0.63</td>
<td>0.76</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>0.74</td>
<td>0.77</td>
<td>0.77</td>
<td>0.76</td>
<td>0.79</td>
<td>1.00</td>
<td>0.76</td>
<td>0.75</td>
<td>0.74</td>
<td>0.64</td>
<td>0.70</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>0.68</td>
<td>0.70</td>
<td>0.74</td>
<td>0.71</td>
<td>0.72</td>
<td>0.76</td>
<td>1.00</td>
<td>0.82</td>
<td>0.79</td>
<td>0.66</td>
<td>0.74</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>0.68</td>
<td>0.73</td>
<td>0.78</td>
<td>0.75</td>
<td>0.74</td>
<td>0.75</td>
<td>0.82</td>
<td>1.00</td>
<td>0.82</td>
<td>0.63</td>
<td>0.68</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>0.71</td>
<td>0.71</td>
<td>0.76</td>
<td>0.77</td>
<td>0.73</td>
<td>0.74</td>
<td>0.79</td>
<td>0.82</td>
<td>1.00</td>
<td>0.71</td>
<td>0.68</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>0.65</td>
<td>0.61</td>
<td>0.65</td>
<td>0.64</td>
<td>0.63</td>
<td>0.64</td>
<td>0.66</td>
<td>0.63</td>
<td>0.71</td>
<td>1.00</td>
<td>0.70</td>
<td></td>
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<tr>
<td>10</td>
<td>0.66</td>
<td>0.69</td>
<td>0.68</td>
<td>0.63</td>
<td>0.70</td>
<td>0.72</td>
<td>0.68</td>
<td>0.68</td>
<td>0.70</td>
<td>1.00</td>
<td>0.69</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>0.74</td>
<td>0.74</td>
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<td>0.75</td>
<td>0.75</td>
<td>0.75</td>
<td>0.82</td>
<td>0.73</td>
<td>0.69</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>

The corresponding fusion result is

$$WSD_{f2} = \sum_{n=1}^{N} w_{f2,n} \cdot WSD_n. \quad (11)$$

4.4 Similarity clustering based EW fusion

The discovery of wake patterns is assisted by similarity based clustering. The fusion algorithm is as follows:

1. Evaluate the similarities between the WSD plots of the central turbine and its neighbors.
2. Determine the similar WSD pairs based on a threshold, which is usually chosen as the saddle point on the histogram of the similarity scores.
3. Group the WSD pairs into clusters, which are not exclusive.
4. The single turbines that are not included in any cluster constitute their own cluster of one.
5. Suppose that there are C clusters. For each cluster, apply the equal-weight fusion to derive the cluster’s fused WSD, denoted by $WSD_c$, with $c \in [1, C]$.
6. Apply equal-weight fusion on $WSD_c$’s to derive the final fusion result, $WSD_{f3}$.

4.5 Similarity clustering based IDW fusion

In this method, EW fusion is applied to members of the individual clusters and then IDW approach is used to fuse the cluster results. Steps 1 to 4 are identical to similarity clustering based EW fusion.

5. Suppose that there are C clusters. For each cluster, apply the inverse-distance-weight fusion to derive a cluster WSD, denoted by $WSD_c$ with $c \in [1, C]$.
6. Apply equal-weight fusion on $WSD_c$’s to derive the final fusion result, $WSD_{f4}$.

4.6 Comparison of the four fusion schemes

The original fusion results are reported in the first column of Figure 9 on Page 9, where the pixel value is in the range of 0 to 1. Some features (valleys and peaks) are not prominent. A histogram analysis for each fusion scheme is shown in the second column of Figure 9, which suggests a
threshold of 0.2 for quantization on the original fusion results. The quantized results are shown in the third column of Figure 9, where the pixel values are in the set of \{0, 1\}, and our automatic procedure can be applied on the quantized fusion results directly, as shown in the fourth column of Figure 9. The automatic procedure measures the azimuth and intensity of the wake. The numerical results are reported in Table 5.

Figure 9 shows that the equal weight fusion may miss some details, and the distance based fusion may incur more outliers. In the similarity-clustering based fusion, depending on what fusion is used within the cluster, the final mixed WSD look similar to either the equal-weight fusion or the inverse-distance-weight fusion.

Table 5: The numerical results of the identified wakes after four fusion schemes.

<table>
<thead>
<tr>
<th></th>
<th>Valley</th>
<th>Left</th>
<th>Right</th>
<th>Spread</th>
<th>Intensity</th>
</tr>
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<tr>
<td>J1</td>
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<td>29.86</td>
<td>99.54</td>
<td>89.68</td>
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</tr>
<tr>
<td></td>
<td>122.30</td>
<td>107.83</td>
<td>137.90</td>
<td>29.86</td>
<td>-0.83168</td>
</tr>
<tr>
<td></td>
<td>203.65</td>
<td>212.39</td>
<td>226.45</td>
<td>14.10</td>
<td>-0.4152</td>
</tr>
<tr>
<td></td>
<td>291.15</td>
<td>274.56</td>
<td>296.96</td>
<td>22.40</td>
<td>-0.48538</td>
</tr>
<tr>
<td>J2</td>
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<td>30.69</td>
<td>140.18</td>
<td>109.49</td>
<td>-0.71445</td>
</tr>
<tr>
<td></td>
<td>211.16</td>
<td>213.18</td>
<td>226.45</td>
<td>13.27</td>
<td>-0.4152</td>
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<tr>
<td></td>
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<td>276.22</td>
<td>286.13</td>
<td>19.91</td>
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</tr>
<tr>
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<td>137.70</td>
<td>107.83</td>
<td>-0.53216</td>
</tr>
<tr>
<td></td>
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<td>212.39</td>
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<tr>
<td></td>
<td>289.91</td>
<td>274.56</td>
<td>296.96</td>
<td>22.40</td>
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</tr>
<tr>
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<tr>
<td></td>
<td>289.91</td>
<td>274.56</td>
<td>296.96</td>
<td>22.40</td>
<td>-0.49123</td>
</tr>
</tbody>
</table>

5 Conclusions

Wakes, often from multiple turbines, cause loss in energy production and complicate the diagnostics of faults. A data-driven approach is proposed using data scatter of wind speed difference versus wind direction. Out of three proposed definitions of wind speed difference, we choose the normalized difference for later analysis, because the normalized difference treats both the low wind speed and the high wind speed in a comparable scale, and the normalized difference is not biased as the ratio difference. In a modern wind farm where hundreds of wind turbines present, an automation of wake analysis procedure is highly demanded. We propose to use morphological imaging operators to identify the azimuth, angular spread and intensity of wakes.

An advantage of our approach is that the multiple wakes do not increase the complexity of modeling as in a physical-model based approach. For each turbine of interest, the pairwise wake patterns between itself and its neighbors are generated and fused in four schemes. In the single-level fusions, the inverse-distance-based fusion avoids the potential over-smoothing in the equal-weight fusion. In the two-level fusions with similarity based clustering, each cluster is treated equally, de-emphasizing the repeated patterns. The fusion scheme within the clusters determines the shape of the fusion results.

The measures associated with the wake’s azimuth, angular spread, and intensity allow us to factor the wake effect into diagnostics and prognostics of wind turbines. Wakes can cause structural loading as well as lower power generation in downwind turbines. Future work includes using the collected information in a probabilistic framework that predicts failures.

References

Figure 6: WSD plots between turbine A and all of its neighboring turbines within a 1000-meter radius.

Figure 9: Comparison of four fusion schemes to derive the mixed WSD and identify the wakes. Each row is one fusion scheme. The first column shows the mixed WSD plots (fusion results). The second column shows the histogram of the first column. The third column shows the quantized fusion results. The fourth column shows the automatically identified wakes.