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Systematic wind farm measurement data reinforcement tool for wake model calibration.

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Abstract

Wind farm wake data analysis is a complex process that requires filtering over many different types of sensors located at different geographical positions. The complexity of the task is increased by the different types of data corruption that can be present. Unfortunately, dealing with wind farm data corruption has rarely been addressed in the literature.
This paper presents different methods intended to reinforce a wind farm dataset. These methods have been applied on several onshore and offshore wind farms.

1 Introduction

Wind farm wake data analysis requires wind information from meteorological (met.) masts inside and outside wind farms as well as the wind turbines status. This type of data gives invaluable information to inspire and validate the development of wake models. However, such a dataset are very complex and composed of hundreds of sensors. The first step of a successful data analysis is to make sure that the data by itself is free of corruption. The term data corruption used here is broad and refers to all the cases where the data values are not equal to what they are intended to represent. This corruption can come from various origins (e.g. sensor incorrectly mounted, measuring device incorrectly calibrated, data conversion errors, sensor failure, obstacles on the wind path, unexpected external conditions).
With the number of wind farms and their respective size increasing, the amount of sensor measurements in databases is rapidly increasing. Consequently, the probability of occurrence of sensor failures or sensor drifting offsets that affect the end goal of the data analysis is also considerably increased. While a preventive methodology designed to mitigate these types of problems is necessary, it is interesting to have as well, robust methods that systematically detect, exclude or correct these events.

While extensive work has been carried out on wind turbine data analysis methods (e.g. the IEC 61400 standards series [1]), the source of documentation concerning specifically wind

farm data analysis is relatively scarce (e.g. Barthelmie [3]). There are no clear guidelines concerning the data corruption that arises when combining several types of sensors located sometimes at several kilometers from each other. In order to mitigate this need, we propose a set of methods to reinforce a wind farm dataset. The methods are based on general knowledge on wind turbine (e.g. DNV/Risø guidelines [5], the Wind Energy Handbook [4]), and the practical wind farm data analysis experience accumulated over several years.

The methods presented are divided into 3 sections. The first section is a recommendation concerning the organisation of the data structure. The second section deals with the calibration of sensors using neighbouring sensors. The last section deals with sensor failure detection and correction.

2   Methods

2.1   Organizing the data structure

2.1.1   Description

A large part of the sensor failure arises human error. And in that part, the data analyst carries a large responsibility. For this reason, it is important to have a data structure that is designed so that mistakes can be spotted and recovered easily. The first generation databases contains the original data supplemented with an individual signal quality parameter. We propose to extend this data structure in order to include the different types of errors detected in the data we investigated.

In order to assess the sensor quality, some neighbouring sensors are generally used. It is interesting to document as well which sensors are associated to a quality check.
Many types of sensors can be subject to time-drifting gain and/or offset. When those values have been determined, they should be stored independently of the raw data.
Similarly, the signals from sensors can be recorded on different monitoring devices which potentially have incorrect or incompatible time and date stamps. So ideally there should also be a way to store the time offset value independently from the raw data.
Eventually, the sensor itself can have a failure or the data can be corrupted numerically. In this case, the raw data itself does not represent any valuable information, but an alternative way to estimate its measurement can potentially be derived using neighbouring sensors. There should also be a way to store this estimation as well as the reference to the method used and the sensors used in that process.

2.1.2   Proposed data structure

- Date & Time and period (e.g. 1-minute, 2-minute, 10-minute)

- Raw data (Mean, Maximum, Minimum, Standard deviation)

- Quality code (with sensors associated)

- Mean gain & offset (when available)

- Time offset

- Corrected data (Mean, Maximum, Minimum, Standard deviation)

- Methods used for correction (with sensors associated)

Storing all this added information increases dramatically the amount information, which represents a significant storing cost. However, having access to all this information is recommended for the long term. It is often seen that, after some time, the engineer responsible for the setting up the database and doing the preprocessing work is no longer available. If the data processing has not been documented both inside the database and on a reference report, the end user is left guessing what has been done, and faced with the extra work to correct data errors.

2.2 Sensor calibration

2.2.1 Wind direction offsets

A wind farm database has generally many accurate wind direction sensors available. However, it is often seen that some of the sensors have not been calibrated properly and operate with a biased offset with respect to the standard wind direction definition. When a reference wind direction is available on site and is believed to be properly calibrated, all the wind direction sensor offsets can be adjusted using the reference sensor.
One particular issue to be aware of during this process is the wind direction dependency to height due to the Coriolis forces. It is important to take this into account when deriving the sensor offset.
Moreover chances are that the offset in wind direction is time dependent. This can come, for example, from a maintenance operation that affected the sensor calibration.

The method proposed to determine a wind direction offset using a reference wind direction is based on a sliding time-window smoothing technique. The difference between the two sensors is plotted with respect to time.
If the difference is noisy, a large time-window is first chosen (typically a week, or a month) to obtain a general idea of the trend of the offset. If an offset jump is spotted during this process, the area of the jump is scanned recursively using a reduced time-window at each step, until an estimate of the offset jump amplitude and the time stamp is determined.
Figure 1 illustrates a very large yaw offset jump between two close turbines.
Estimating a robust reference wind direction can be difficult, especially in offshore context where access to the site is limited. Several types of information can contribute to determining the offset of a wind direction sensor. For a wind turbine yaw sensor, the wind turbine power production and geographical location can potentially provide a way to determine an offset. This can be done by calculating the mean power ratio of two aligned turbines, with the first turbine having a free stream wind direction. If the turbines are relatively close (e.g. between 2 and 10 rotor diameters), a distinct power deficit caused by the wake of the first turbine on the second one can be measured at wind speed corresponding to high C_T (e.g. 5-10m/s). It is possible to estimate with a few degrees accuracy the yaw sensor offset by running an average smoothing algorithm or fitting a Gaussian distribution. In order to avoid missing time dependent offsets, this process can be carried on a sliding time window.

For a met. mast, the same procedure as for the yaw sensors can be used, if some wind turbines are located at a relatively short distance to the met. mast.
Figure 2 illustrates this method by comparing the wind direction sensor of a met. mast with the power ratio of two close turbines on the edge of the wind farm (on the first and second row) aligned in the direction of the free stream wind speed.
Note that if the met. mast is located in close periphery of the wind farm, there might be
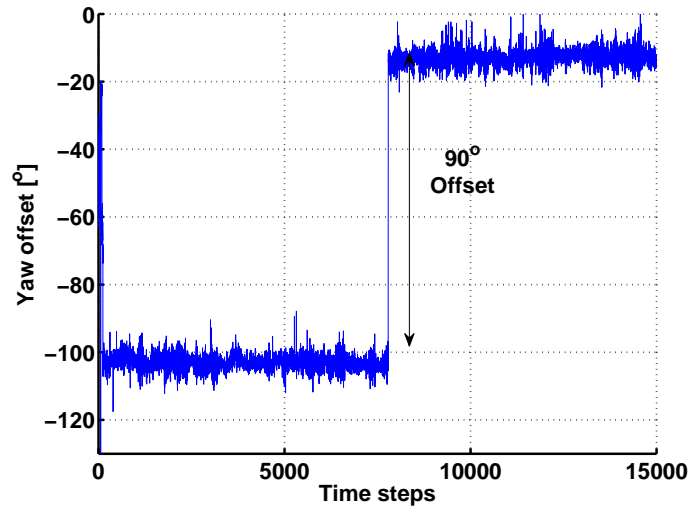
Figure 1: Yaw difference between two close wind turbines.

some park effects affecting the local wind speed and direction (e.g. blockage effect). This method might then give an offset dependent with wind direction.

If the mast schematics are available, the position of the sensors on the mast can also provide a way to determine the wind direction offset. The idea is to use a wind speed measurement sensor (e.g. cup anemometer, sonic anemometer) that is not placed on top of the met. mast, to determine the offset of a wind vane on the same mast. The method is to plot the turbulence intensity for different wind speed bins, with respect to the wind direction. This plot should present a peak in the direction angle corresponding to the shadow of the met. mast seen by the anemometer.

In order to spot a potential dependency of the offset with time, this method should be applied over a sliding time window. Figure 3 illustrates a small dependency of the offset with time that was observed on an offshore met. mast. There are 3 visibly distinct peak angle locations over time, where the offset jump is between 2 and 4 degrees.

As mentioned before, the relative height between the two sensors is an important parameter, since the wind direction is expected to be height dependent.

In this method, one has to be careful not to mistake the wind farm added turbulence intensity with the met. mast shadow turbulence intensity.

2.2.2   Time offsets

Time offsets generally occur when measurement from several different recording devices are gathered in the same database. If the recording devices were not synchronized to the same time, and the time offsets were not corrected during the gathering process, the resulting database is unusable. It can sometimes be a rather small time offset (e.g. a few hours) which can be difficult to detect, but large enough to corrupt the data analysis.

In order to determine precisely the time offset, we propose to use the time correlation
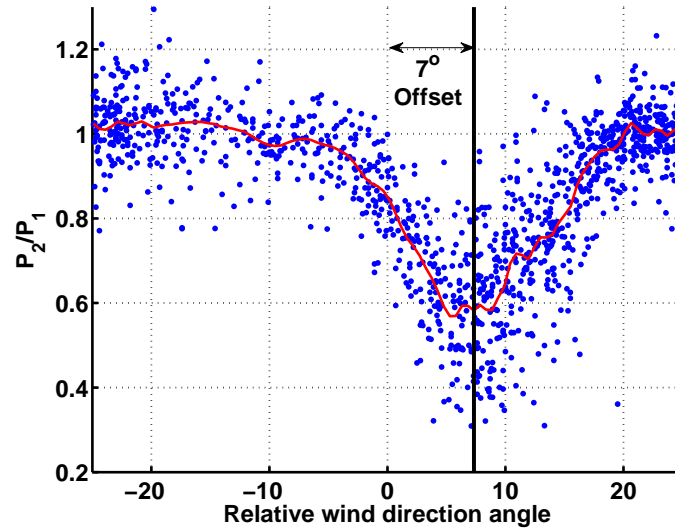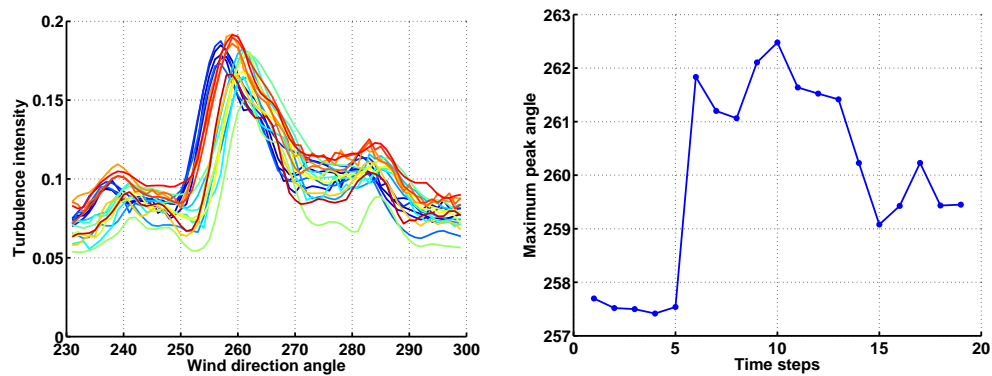
Figure 2: Power difference between two close wind turbines compared to a neighbouring met. mast wind vane. The wind direction is centered on the wind turbines alignement direction angle.

(a) Turbulence intensity versus the wind direction measured on a met. mast at different time periods. The peak corresponds to the shadow angle of the tower.

(b) Time history of the maximum turbulence intensity peak angle location

Figure 3: Illustration of a small time drifting wind vane offset on an offshore met. mast
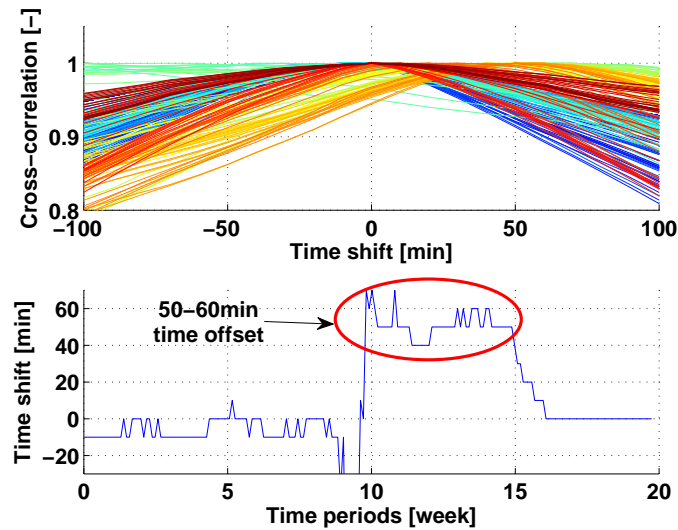
Figure 4: Time offset found in a wind farm by comparing a nacelle anemometer and a met. mast anemometer. The top plot is the cross-correlations between the two signals. The bottom plot is the time history of the cross-correlation peak location, indicating the time offset. The signals are 10min means, therefore the cross-correlation precision is 10min, which explains the spikes. There is a clear time offset of 50-60min during 5 weeks.

between two similar neighbouring sensors located on different recording devices. The time correlation function indicates how the two sensors are correlated with respect to the time offset. If the two sensors are next to each other and synchronized to the same time, the correlation function has a maximum peak at 0 seconds. If there is a time offset, it is indicated by the maximum peak location. As this time offset can also be time dependent, it is necessary to do a sliding time-window analysis in the same fashion described in the previous section.

Figure 4 shows a time offset between a nacelle anemometer and a met. mast anemometer. The two sensor data were originally recorded on two different systems and gathered manually every month. During one month an offset of 50-60 minutes was apparently introduced by a careless operation.

Note that the time correlation is related to the distance between the two sensors and the wind speed. As most of the relevant information are convected by the wind, if the sensors are located far apart, and/or the wind speed is small, it might be that the time for the information to reach the second sensor is greater than the 10-minute averaging time window. In that sense, an offset found to be under 20 minutes in a wind farm has to be treated with caution. In Figure 4, the time offset has a precision of 10 minutes and oscillates between 0-10 minutes in the first part. As the two sensors where located far apart, it is expected that their relative time offset should be between 0-10 minutes.

2.3 Sensor failure

The type of sensor failure of interest here is when a sensor is producing a value which is unexpected from the values of other related neighbouring sensors. The idea is that each

sensor should be related to some neighbouring sensors through a specific model within a degree of uncertainty.

For example, wind turbines, when they are not externally controlled, have usually a rather predictable control algorithm. In most cases, there is a clear correlation between some of the main sensors (e.g. Power, RPM, Pitch angle can all be reduced to a function of wind speed).

If there is a sensor that suddenly loses this correlation, the chances are that the sensor has failed or that the external conditions are no longer "normal" (e.g. exceptional wind condition, wind turbine shut down).

The challenge is, therefore, to determine a set of robust rules that associate each kind of sensor with its neighbouring sensors. Depending on which rule is violated, an action is determined. For example, not using the sensor or using an estimate of the sensor based on its neighbouring sensors. Individual power curves based on the the nacelle wind speed for each individual wind turbine can be used to qualify the power recordings or to eliminate outliners (e.g. start/stop sequences, anemometer errors).. First generation rules for screening wind speed measurements have been formulated in [2].

2.3.1   Met. mast anemometer

Anemometers mounted on met. masts are meant to record the local wind speed but might experience systematic bias under specific conditions. It is therefore interesting to determine when those conditions occur and to adopt an appropriate mitigation method.

One of the most important issues with met. mast anemometry is caused by the met. mast itself. If the anemometer is not mounted according to the standards [1], the anemometer might be systematically biased. For a data analyst who does not have access to the site, it is difficult to estimate when this occurs. The best way is to compare with different wind speed recordings mounted on the same met. mast or at different locations and mounted in a different fashion.

Even if the anemometer is mounted according to the standards and if the anemometer is not mounted at the top, some wind directions yield a configuration where the anemometer is downstream of the tower. As it was described in the Wind direction offset Section, this phenomena can easily be determine by plotting the turbulence intensity with respect to the local wind direction. The peak indicates the wind direction angle where the wind speed measurements are affected by the met. mast tower shadow. In these wind directions it is preferable to use another anemometer on the same mast, at the same height, and not located in the tower shadow.

Cup anemometers are instruments with a rotating part. The grease or oil used to allow this motion naturally introduces a viscous moment opposite to the motion. The recordings are calibrated in a wind tunnel or in a met. test station to partly estimate this viscous moment. The problem is that the oil or grease used in the anemometer has a viscosity property dependent to the temperature and humidity. For example, under cold conditions the anemometer become iced and can completely stop working. These events can be spotted using the temperature sensor.

Other important failure types is lightning strikes, which can partly damage the bearings but such errors can be very difficult to identify. A proper data screening procedure is needed

[2].

When a met. mast anemometer recording cannot be trusted, we recommend using the information from the other met. mast anemometers to estimate the correct wind speed information. At the sites we considered the terrain effects were minimum, and the undisturbed wind profiles are modelled relatively easily using the surface roughness and standard atmospheric stability parameters. In those cases, when only one anemometer failed it was possible to estimate the measurement using an interpolation of the wind profile given by the other anemometers mounted on the same met mast.
The main difference is that their recordings are not influenced on such a big scale.

2.3.2 Met. mast wind direction

Most of the recommendations above for anemometers are also valid for wind vanes. Measurements are also influenced by the met. mast itself, how they are mounted on it, and the ambient temperature. Extreme temperatures may alter the wind vane reaction speed.
Spotting the met. mast shadow is also a bit more difficult. One way could be to try to see if there is a clear peak on the wind direction standard deviation when plotted against the wind direction. If this was not the case, we assumed that the wind direction sensor could be trusted even under the mast shadow.

When a wind direction sensor fails, we suggest to use the combined information from different wind vane sensors located on the same met. mast, or at a close distance. During this process it is important to keep in consideration that the wind speed is height dependent.

2.3.3 Wind turbines main operational sensors

The main operational sensors that are generally accessible on modern turbines are:

- Electrical power output

- Rotor rotation per minute (or eventually high speed shaft rotation per minute)

- Blade pitch angle

- Nacelle yaw direction (or yaw misalignment combined with the wind direction)

- Nacelle anemometer

- Eventually some strain gages to measure loads on different parts of the turbine (blades, tower, shaft)

The wind turbine control system of most modern wind turbines can be simplified on a 10-minute period to a simple relationship between the inflow wind conditions and all the operational sensors. However, because of the wake effect, the wind turbines inside a wind farm see a large variety of incoming flow conditions. In order to detect a sensor failure, it is ideal to know the complete incoming wind speed profile and to conduct a simulation of the wind turbine associated behavior. Unfortunately, in most cases, there is only a nacelle anemometer (placed downstream of the rotor) and a yaw sensor to estimate those different kind of inflow wind profiles. Nonetheless, we found that it was in most cases acceptable to use only the nacelle anemometer to generate a robust sensor curve. By using a sensor curve with respect to the nacelle anemometer, with an appropriate error acceptance, is is possible to effectively spot the exceptional events when the sensor (or the nacelle anemometer) is not recording a normal condition.

When one of the sensors on the wind turbine indicates a potential failure, the safest action is to ignore the specific 10-minute data, as there are good chances that they indicate a time when the wind turbine did not operate under normal conditions. But if this represents a significant amount of data, it might be necessary to determine if this is indeed a recording failure, and that the wind turbine was actually operating normally. In this case it is better to deactivate the pre-filter based on this sensor during a manually set time period.
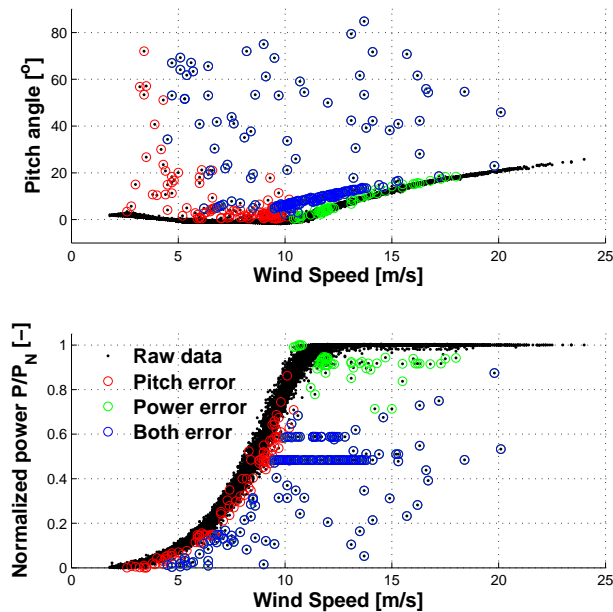

Figure 5: Outliers on the pitch and power curves. The outliers are found by computing the distance between the point and the corresponding averaged value. Some outliers on one curve are not found on the other curve.

Note that this method is not sufficient to filter out the cases when the wind turbine is externally controlled, for example when the grid operator wants to reduce the power fluctuation on its network. If the wind turbine is systematically externally controlled, the original sensor curve might be completely blurred by the external control. In that case it is necessary to have an indication of when the external control happens.

Figure 5 illustrates this method on the pitch and power curve of a wind turbine in the middle of an offshore wind farm. Some of the outliers found with one curve are not found on the other curve.
The outliers spotted in this example represents roughly one percent of the wind turbine data, when the wind turbine is working without external control. However, as each of the wind turbine operates to a large extend independently, applying this criteria to the whole wind farm can reduce dramatically the amount of data remaining. For example, the probability that 100 wind turbines operate under optimum conditions at the same time, when each

turbine has a reliability of 99% is $P = 99\%^{100} = 36.6\%$. For this reason, it might not be the best solution to apply this method on all the turbines at the same time.

3   Conclusion

Different methods have been presented in order to reinforce and to organize a wind farm dataset. Such methods are particularly adapted to wind farm wake analysis and wind farm performance estimation.
The methods have been applied with success on several wind farm datasets.
As the different sensors have independent probability of failure, the added probability that all the sensors are operating under normal conditions at the same time becomes very unlikely as the number of wind turbine and met. mast considered increase. A compromise has therefore to be made between the quality and the quantity of data considered for the analysis.

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