ACTIVE WAKE CONTROL VALIDATION METHODOLOGY

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EXECUTIVE SUMMARY

Active Wake Control (AWC) has reached the point of industrial application in offshore wind farms. Yawing the upstream turbines to deflect the wake is the method currently being focussed upon. The optimized yaw settings will naturally differ depending on the wind farm, as the wind conditions and farm layout vary. The increase in the annual yield is expected to reach 1%, although variations may exist depending on the farm. Active Wake Control design and implementation, a farm dependent feature, needs to be validated with an independent method so that key stakeholders have confidence in implementing the control solution and clarity on the business case.

Siemens Gamesa Renewable Energy (SGRE) is the first offshore wind turbine manufacturer to offer a commercial product for AWC and is, together with offshore wind farm Sandbank (and others) performing trials of their solution 'Wake Adapt'. In project Dyscon, TNO has been given access to the Sandbank pilot project data and has developed and tested its independent methodology for validating wind farm control benefits by comparing measured data with and without AWC applied.

The key starting point for the validation methodology developed and tested in Dyscon are the existing sensors in the wind farm, which are commonly used. This means working with the inherently limited sensors behind the rotor wake, which gives rise to technical challenges such as data quality in validating AWC. An additional challenge is the quantity of the data, as pilot projects in offshore wind farms are subject to limitations by the Transmission System Operator (TSO).

The validation methodology tackles the challenges of both data quality and data quantity. The benefits of not having to retrofit additional sensors and adding cost and complexity to wind farms already under pressure to deliver the lowest cost of energy are significant.

The methodology has proved its potential and usefulness in validating AWC in the first comprehensive offshore pilot project for yaw based control.

MOTIVATION

Wake effects inside a typical offshore wind farm are known to lead to high power production losses depending on the specific layout and wind conditions. The wake refers to the altered wind after travelling through a wind turbine rotor. More specifically, as one turbine extracts energy from the wind, the wind speed will decrease and the turbulence intensity increase. In a wind farm, the first row of wind turbines, i.e., the row of turbines that faces the incoming wind, will extract the most energy from it. Turbines downstream of this row, though, will have less energy available in the wind to produce power. The latter will therefore generate an amount of energy that is reduced when compared to what would be expected if a wake would not be present.

The aerodynamic interaction between turbines can fortunately be actively manipulated, i.e., the wake characteristics can be altered so that turbines downstream are not hampered as vigorously. TNO refers to this as 'Active Wake Control (AWC)' and dates back to its awarded two patents already achieved in 2003. The technique relies on changing the upwind turbines control settings, which leads to power losses in the upstream row of turbines, but power increases in turbines downstream with a net positive effect on power production of the farm as a whole. The current accepted benefits for offshore wind farms are between 0.5 and 1% increase in annual power production for a typical offshore wind farm, which equates to multimillion additional income from the electricity production over its lifetime. The wind farm turbine loading is also expected to reduce and this can have economic benefits on operation and maintenance.

The two patented techniques have been widely studied for the past decades. The first focuses on deflecting the direction of the wake and the second in changing the velocity deficit of the wake. In the first (referred to as wake redirection control), the direction of the wake is changed by purposefully misaligning the rotor of the upstream turbine with the direction of the incoming wind, generating a lateral force which drives the wake to the side. Consequently, downstream turbines' rotors will have less overlap with the wake. In the second, referred to as axial induction control, the wake is modified by changing the control settings of the upstream turbine so that more kinetic energy is left in the wake to increase power production of the downstream turbine.

TNO (The Netherlands Organisation for Applied Scientific Research), (historically with Energy research Centre of the Netherlands (ECN)) is a pioneer and leader in the topic of AWC. As mentioned, patents were already granted in 2003. Since then extensive R&D has been completed to increase the technology readiness level of wind farm control and decrease the risks associated with its application in the real world. Fast forwarding to 2019, the wind farm control technology was licensed to SGRE and forms a part of the SGRE product 'Wake Adapt'.

Implementing AWC in critical energy infrastructure is not straightforward despite the strong and founded beliefs in the positive benefits.

Data quality is one of the challenges, as the measurements in commercial offshore wind farms are taken using available sensors disturbed by the rotor. Data quantity is another of the challenges. Unavailable or curtailed turbines need to be dealt with in a proper manner to avoid high data rejection whilst at the same time ensuring accurate results. Furthermore, given the novelty of employing AWC in large scale farms, different approaches can be taken when designing the methodology for validation, which can naturally lead to distinct results. It is therefore important that an independent and ideally robust methodology is designed. This is where TNO steps in, given its expertise in wind energy, AWC and having independence as a core value.

At the time this methodology was developed, no data from an offshore wind farm AWC campaign existed. Therefore, to compare the performance of a wind farm under normal operation and AWC, the Supervisory Control And Data Acquisition (SCADA) data set from an existing wind farm was simply divided into two equal data sets under normal operation. This allowed to verify the approaches taken and evaluate their suitability before applying the methodology to the final data set from the AWC campaign.

The first test used 2.5 years of SCADA data from Anholt, a Danish offshore wind farm located between Djursland and the Island of Anholt, approximately 12km off the Danish shore. Operated by Ørsted, the wind farm consists of 111 Siemens wind turbines of the type SW-3.6-120 (rated power of 3.6 MW and rotor diameter of 120 meters). The wind farm has a total capacity of 400 MW.

The second test used 2.5 years of SCADA data from Westermost Rough, an offshore wind farm located 8km of the English shore, in the North Sea. Operated by Ørsted, the wind farm consists of 35 Siemens wind turbines of type SWT-6.0-154 (rated power of 6MW and rotor diameter of 154 meters). The wind farm has a total capacity of 210 MW.

The methodology is being applied already to a measurement campaign where a full scale testing of Wake Adapt, Siemens Gamesa Renewable Energy (SGRE) first of its kind AWC commercial software is being undertaken in an offshore wind farm off the coast of Germany in the North Sea. The offshore wind farm, Sandbank, is comprised of 72 Siemens SWT-4.0-130 (rated power of 4.0MW and rotor diameter of 130 meters) and has a total capacity 288 MW. The Sandbank offshore wind farm was developed as a joint project between Vattenfall and Stadtwerke München.

This document describes the developed validation methodology, focusing on its requirements, different steps within the methodology and the approaches taken for the various existing and known challenges.

THE ACTIVE WAKE CONTROL VALIDATION METHODOLOGY

(WITHOUT ADDITIONAL SENSORS)

The Active Wake Control validation methodology quantifies the increase in the Annual Energy Production (AEP) which is gained by making use of AWC. It makes use of measurements collected from a campaign and requires available on-site measurements only, i.e., it was designed such that no additional measurement devices besides the ones typically available and already in place in wind farms are needed. The methodology is specifically developed for AWC by wake redirection control, albeit being readily applicable to induction control with small modifications.

The AWC validation methodology has been designed to fulfil various requirements, namely:

- It must be applicable to large offshore wind farms of any layout.
- It shall not assume availability of historic data.
- It shall include a method which makes use of data retrieved from a measurement campaign involving the available on-site measurement equipment only.
- It shall use SCADA data, as a minimum requirement, at time intervals of 10 minutes (10 minute statistics). Higher frequency data may also be used, if deemed necessary.
- It shall not make use of simulation models to fill in missing data in the measurements.
- It shall make use of data from trials with a maximum duration of one year. The measurement campaign might consist of a number of shorter periods of several months, with the accuracy increasing after each period.

The above requirements give rise to the validation methodology, which is, at its core, comprised of the various sections that follow, each one properly addressing the inherent challenges in using generalised SCADA data from a wind farm for validation purposes of AWC.

The method goes through the following main steps:

A. Determination of wind velocity using nacelle anemometry and the consensus wind speed (incoming undisturbed wind speed measured by the leading turbines in the farm).
B. Determination of wind direction using nacelle anemometry and the consensus wind direction (incoming undisturbed wind direction measured by the leading turbines in the farm).
C. Rejection of data points that do not meet quality standards.
D. Binning the different data points according to the pre computed consensus wind speed and wind direction.
E. Calculation of the wind farm power ratio of each of the wind sectors, which is then followed by the calculation of the annual weighted average wind farm power ratio based on the wind speed and direction frequency distribution.
F. Quantification of overall uncertainties, following the definition of category A and category B uncertainties used in the IEC 61400-12-1:2013 *(International Eletrotechnical Comission, 2013).*
G. Assessment of benefits of AWC operation at the turbine level, by comparing the weighted power ratios between nominal and AWC operation for the different wind sectors.

A. DETERMINING WIND VELOCITY USING NACELLE ANEMOMETRY

How to determine the wind velocity using nacelle anemometry?

The first step ensures that wind speed measurements taken using nacelle anemometers are comparable in nominal operation and AWC operation.

(Motivation) The ideal measurement signal to be used for the purposes of validation would be the free stream wind speed. Alas, there exists no guarantee that such signal is available, as it presumes the existence of a met mast or LiDAR, which may not be present. It becomes then necessary to use the nacelle based measurement of the wind velocity, which is taken behind the rotor and is disturbed by the rotor blades, hub and nacelle.

The wind speeds measured at the wind turbines' nacelles are then used. In AWC operation, however, the yaw misalignment will bias the measurements, as the nacelle wind speed and wind direction measurements are biased by the rotor wake. A relationship between the nacelle-based wind speed measurements during operation with yaw misalignment and that during nominal operation without yaw offset needs to be constructed. This relationship is labelled within the context of TNO's validation methodology as Wind Speed Transfer Function (WSTF). To establish this relation an extensive set of measured data under controlled conditions needs to be collected by at least one turbine operating with intentional yaw misalignment and at least one neighbouring turbine operating nominally, where both operate in free stream.

Figure 1 exemplifies the procedure for deriving the Nacelle Transfer Function (NTF) (in the absence of other neighbouring turbines operating nominally, the met mast measurements are used, which comes down to computing the NTF as per the IEC 61400-12-2, instead of the WSTF). Measurements from an experiment where a GE 1.5 MW turbine was operated with intentional misalignment are used in this example, from the EU H2020 Closed-loop wind farm control (CL-Windcon) project. Figure 1 shows the WSTF for the yaw error bin of -20 degrees. The nacelle-based wind speed measurements were binned (represented on the x-axis), and for each bin the corresponding met mast wind speed measurements were averaged (represented on the y-axis). This binning yields the NTF for a given yaw error bin, relating the nacelle-based wind speed and met mast measurements using piece-wise linear functions.

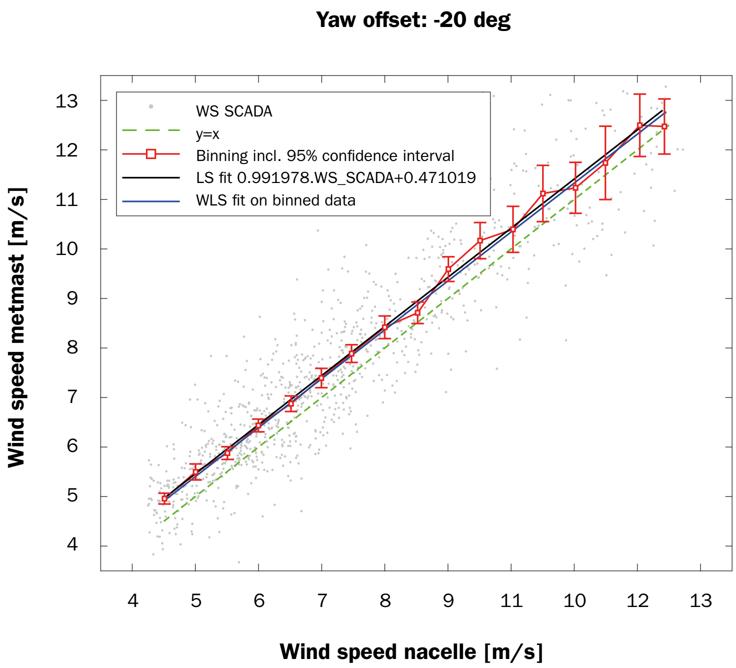

Figure 1 *Example of the procedure used to compute the Nacelle Transfer Function for a yaw angle misalignment of -20 degrees, relating the wind speed nacelle measurements (binned and represented in the x-axis) with the wind speed at the met mast (averaged for each bin and represented in the y-axis) (Kanev, 2020).*

The constructed WSTF can then be used to correct wind velocities measured at the yawed turbines during AWC tests, making measurements consistent with reference measurements without yaw misalignment. Whenever the WSTF is provided, the methodology requires this to be checked for validity.

The methodology does not impose as a strict requirement the use of a WSTF, it merely suggests its construction in the baseline setup, i.e., only SCADA data is made available. In addition, currently less conventional wind measurements, available at a given site, may be used instead, such as (but not limited to):

- Nacelle-based forward looking LiDARs.
- Hub-mounted measurement devices (such as the ROMO wind spinner anemometer iSpin, or LiDAR systems).
- Rotor-effective wind speed estimate, derived using operational data other than (or in addition to) the nacelle-based anemometer readings.
- SoDAR or LiDAR remote sensing systems measuring the incoming free stream wind conditions, located on substations, transition pieces, or nacelles.
- Upward-looking floating LiDAR systems installed on various locations to cover all relevant wind directions.

Following the derivation of consistent nacelle-based wind speed measurements compensated for the effect of yaw misalignment, a single wind velocity signal representing the incoming wind speed for the whole wind farm is constructed. This signal is used in the process of binning the data at a later stage. This signal is labelled as consensus wind speed, V_{cons}, and is taken as the average value of the wind speed measurements at all wind turbines operating in free stream (as identified by a simple but conservative wake expansion model, such as the Jensen model).

B. DETERMINING WIND DIRECTION USING NACELLE ANEMOMETRY

How to determine the wind direction using nacelle anemometry?

The second step guarantees that wind direction measurements using nacelle vanes are accurate and comparable in both test cases. For that, nacelle measurements are corrected to avoid biases under yaw misalignments.

(Motivation) The ideal measurement signal to be used for the purposes of validation would be the free stream wind direction. In the same line of reasoning used for the wind speed free stream measurement, the conventionally available nacelle orientation measurement in combination with the yaw error measurement (i.e., nacelle-based relative wind direction) are used to construct the true wind direction measurement, as the methodology is designed under the assumption that only equipment already available on site shall be made us of.

At present, the conventional nacelle direction measurements are only used for monitoring the cable twisting in order to activate the untwisting sequence when necessary, and this process does not require a precise measurement of the nacelle position with relation to the true north. As a result, currently used nacelle direction sensors are often biased, and in some systems drifts and/or abrupt changes may be present.

Consequently, nacelle orientation measurements are first calibrated before being used to assess AWC. This is a necessary step as such measurements are known to exhibit a time varying bias in some commercial turbines. The calibration procedure is achieved by means of a power deficit analysis using data from nominal operation without intentional yaw misalignment. The idea underpinning the approach uses the power ratios between the measured power production of the to-be-calibrated wind turbine and another (ideally adjacent) wind turbine, both operating in partial load, i.e., below rated wind speed. A dip in the power ratio should be noticeable in the wind direction where the two turbines are aligned. The nacelle direction reading, due to the existing bias, will be different than the orientation determined from the position of the two turbines in the farm layout. Therefore, it can then be calibrated to achieve this condition. This procedure is significantly simplified if a wake model is used in combination with the measurement data, where the power ratio is modelled using a wind farm model, as exemplified in Figure 2. At TNO, our own in house cutting-edge software tool, FarmFlow, is used to model wake effects *(Edwin Bot, 2020)*. FarmFlow is an extensively validated tool which achieves very accurate results at acceptable calculation time.

A test using SCADA data over a period of 2 years (Nov 17' to Nov 19') from an offshore Wind Farm was performed to assess the calibration procedure. The offshore wind farm is Gwynt y Mor, composed of 160 Siemens SWT-3.6-107 (3.6 MW with a 107 rotor diameter) wind turbines. The test made use of 17 adjacent turbines located at the most south position of the farm to calculate the calibration offset over a total period of two years. For the 17 turbines, different calibration offsets were determined. The minimum value for the offset found, in absolute terms, was 0.94 degrees, and a maximum of 20.93 degrees. The values ranged between these two, with an average absolute offset of 5.74 degrees. The calculation of the offsets was performed onto 4 separate time windows, by having divided the 2 year period into 4 semesters. Comparing the offsets calculated for each turbine through the different time intervals, it was seen that the maximum deviation between the average of the four intervals and the actual values is not higher than 1.5 degrees (20% of the absolute average offset of 7.5 degrees), showing that the procedure is robust. These results are summarized in Table 1.

Similarly to the WSTF, a Wind Direction Transfer Function (WDTF) can then be constructed, relating the wind direction measurement during intentional misalignment and that during nominal operation. Its construction follows the same procedure as the WSTF, requiring data from at least two neighbouring turbines operating in free stream and one of the two with intentional yaw misalignment. In case the WDTF is provided, it should be checked for validity. Other measurement devices or calibration procedures may be used for acquiring wind direction measurements.

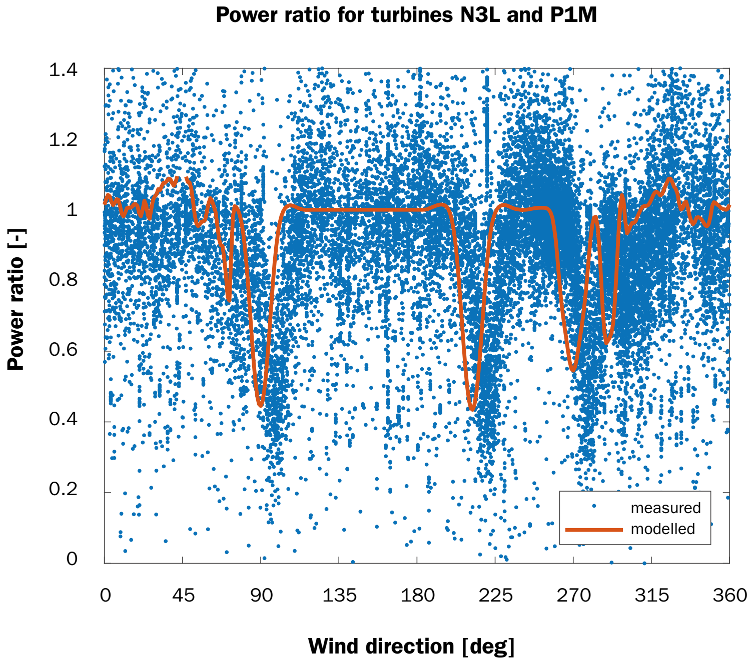

Figure 2 *Power ratio between two neighbouring turbines from Gwynt y Mor Wind Farm. The measured and modelled dip in the power ratio is noticeable, quantifying the bias to be used for the nacelle wind direction measurements correction (Kanev, 2020).*

Table 1 *Variation of the calibration offset, in degrees, over the 4 periods in which the data was divided and for the 17 turbines used in this study. The penultimate column shows the average calibration offset for the four periods and the last column the maximum deviation from the average, in absolute values.*

Turbine ID	**Period 1** [deg]	**Period 2** [deg]	**Period 3** [deg]	**Period 4** [deg]	**Average** [deg]	**Max dev** [deg]
M1M	-5.76	-5.27	-5.03	-6.15	-5.55	0.60
M2M	3.56	1.51	2.33	2.05	2.36	1.20
M3L	-2.48	-3.05	-3.43	-3.65	2.36	0.67
M4L	-15.81	-16.27	-17.17	-17.63	-16.72	0.91
M5L	2.53	2.15	2.21	0.94	1.96	1.02
N1M	-10.18	-10.84	-11.61	-11.06	-10.92	0.74
L4L	-19.66	-20.52	-19.84	-20.93	-20.24	0.69
K6K	7.62	6.68	7.38	6.27	6.99	0.72
J8K	5.01	4.03	4.22	3.22	4.12	0.90
H9K	-4.18	-5.55	-4.74	-3.55	-4.51	1.05
P1M	-7.32	-7.4	-9.23	-8.8	-8.19	1.04
N3L	12.46	11.72	11.15	10.66	11.50	0.96
L6L	-3.76	-5.71	-4.75	-5.26	-4.87	1.11
K8L	4.2	2.51	3.07	3.47	3.31	0.89
J10K	-9.09	-9.19	-9.71	-11.05	-9.76	1.29
K5Q	-10.15	-11.88	-10.96	-11.41	-11.10	0.95
K7K	-2.16	-2.78	-2.68	-4.17	-2.95	1.22

Following the derivation of consistent nacelle-based wind direction measurements where the effect of yaw misalignment is compensated for, a single wind direction signal representing the incoming free stream wind direction for the whole wind farm is constructed. This is analogous to the consensus wind speed calculation and this signal is likewise used in the process of binning the data at a later stage. This signal is labelled as consensus wind direction, α_{cons}, and is again taken as the average value of the wind direction measurements at all wind turbines operating in free stream.

C. FILTERING THE DATA

What filtering should be applied to the data and what measurement points should be considered for the final assessment of AWC?

The third step identifies the data points that should not be used for the final assessment. These points comprise instances where turbines are not producing power, have been curtailed, power boosted or do not meet certain quality standards.

(Motivation) Using SCADA data from an offshore wind farm in operation presents many challenges. Sensors may fail or degrade (e.g. due to icing) and certain settings of the turbine may invalidate the assessment of AWC (curtailment, power boosting). Furthermore, the methodology should also carefully select which time instants to use based on the transient behaviour of the wake during the toggling between modes of operation. To ensure that the employed methodology truly assesses benefits of AWC, proper filtering of the data points is necessary. The following filtering criteria are applied.

Filtering based on operating conditions

Measurements where turbines are producing power below a certain minimum threshold, are curtailed or power boosted are suggested to be removed from the analysis. Moreover, downstream turbines in the wake of the identified ones are also removed from the analysis.

The methodology accepts time records containing unavailable turbines, as rejecting these would be too restrictive and lead to a high number of rejected instants. It only restricts time instants to have a minimum number of normally operating wind turbines (e.g., 10% of all). It further ensures that turbines are available, i.e., that they are in power production mode, by accepting measurements points where power production is higher than a pre-defined value (e.g., 1% of rated power.)

Turbines in a certain 10 minute instant are rejected if they are curtailed. This is necessary as the comparison between nominal operation and AWC, for the same turbine, cannot merge different conditions, such as curtailed and uncurtailed. Nevertheless, if the curtailment is activated in a pre-defined fashion and is consistent throughout the complete campaign, the turbine may not need to be removed from the analysis.

Turbines power boosted in an inconsistent manner throughout the campaign are similarly rejected. This procedure is analogous to the rejection based on curtailment. Nevertheless, power boosting that is consistently applied to given wind turbines (in specific wind speed and direction) independent of the farm mode of operation, may be included in the analysis.

On top of the aforementioned selective criteria, all turbines in the wake of non operating turbines, curtailed or power boosted are treated equally, i.e., removed from the analysis. To determine these turbines, a simple but conservative wake expansion model is used.

In the event that a high rejection of measurements is observed due to many turbines being curtailed or unavailable, the previous downstream turbine rejection criteria may be relaxed. This relaxation, in practical terms, translates in only rejecting turbines up until a certain distance downstream, such as 20 or 30 rotor diameters of the flagged turbine. A wake expansion model is here again used. This approach leads to lower data being rejected, which is of special relevance for wind farms which have long rows of turbines.

Filtering based on instrumentation

The methodology requires measurements to be consistent throughout the campaign. In practical terms, the methodology requires that the measurements taken (wind speed, wind direction and power, for example) are performed using the same sensors. As an example, in case a power estimator is used as the most relying method to retrieve the power production measurement, then all measurements for which the estimator was not available will not be considered for the final analysis.

Filtering based on measurement quality

To ensure maximum quality of the measurements, the methodology recommends that at least 10 minutes of the measurement data is skipped from the analysis after changing the mode of operation. This procedure allows to exclude possible transients related to yaw and wake dynamics.

Furthermore, measurement points that have high values of standard deviation of the consensus wind speed and consensus wind direction are rejected from the analysis. The limits of these two conditions need to be chosen in order to strive a balance between the quality of data and the exclusion of measurement points. It is recommended to keep this threshold lower than the wind speed and wind direction bin sizes (to be used in the next step of the methodology).

Figure 3 sheds light to the workings of the different steps discussed until this point. The identified leading row of turbines which faces the undisturbed inflow is represented in green. In each, the wind speed measurements and (calibrated) wind direction measurements are written on top. Taking the average of these, the consensus wind speed and direction are computed, which should represent the incoming wind characteristics. Notice that one of these turbines, represented in grey, is unavailable. For this time instant, the turbine is not taken into account to compute the consensus wind speed and direction.

For the depicted example, measurements fall more or less within the same boundaries, i.e., they do not oscillate much. The consensus wind speed would be 8.965 m/s with a standard deviation of 0.153 m/s. The consensus wind direction would be 91.905 degrees with a standard deviation 1.235 degrees. The standard deviations of the consensus wind speed and direction would make this time instant suitable in terms of quality standards.

Immediately in the second row, a curtailed turbine is illustrated in orange. Measurements from this turbine at this instant are removed from the analysis. Records from the turbines in the wake of the curtailed one are likewise removed for the final calculations. The wake is represented in light blue. It is possible to only exclude turbines up until a certain distance downstream, as it is expected that the flow recovers to normal conditions. This flexible parameter is sketched with the letter D, referring to the distance, in rotor diameters, for excluding downstream turbines, illustrated in yellow.

Other turbines that may be excluded are, for example, power boosted turbines (if not independent on the mode of operation). These are shown in red and are excluded from the analyses. Turbines downstream of these, represented again in yellow and identified through the wake expansion model, are similarly to turbines downstream of curtailed turbines, excluded from the analyses.

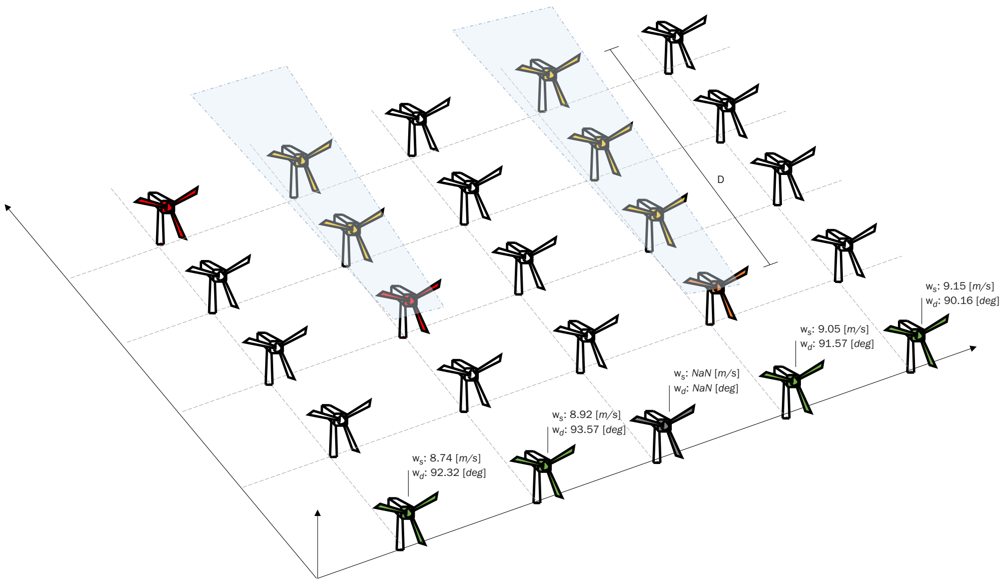

Figure 3 *Schematics illustrating the first three steps of the methodology: determination of consensus wind speed, consensus wind direction and filtering using wake expansion model (light blue).*

D. BINNING THE DATA

How to bin the data to ensure sufficient number of data points in each bin?

The fourth step guarantees that each wind speed and direction sector will have sufficient number of points so that the uncertainty of the bin is maintained within desired levels.

(Motivation) The data needs to be attributed to a certain wind direction range and wind speed range, usually referred to as the process of binning, i.e., segmenting the different data points into specific groups. This process may lead to having certain bins with insufficient number of measurements and large uncertainties. On the other hand, increasing the sizes of bins affects the assessment of AWC since the variations in power within the same bin become too large, generating high uncertainties again.

To overcome the indicated trade-off, the methodology uses a varying size bin approach, i.e., during the binning procedure, the sizes of the bins are varied according to pre-defined criteria.

The first step is to declare the initial bin size for wind speed and wind direction. As a baseline recommendation, it is suggested to keep the bin size for the wind velocity fixed at 1 m/s and vary only the wind direction size, increasing it from 1 degree to a certain maximum wind direction bin size. The values for wind velocity and wind direction are the already computed consensus wind speed and consensus wind direction.

The second step consists in defining the desired uncertainty and the maximum allowable uncertainty within a certain bin. These two correspond to a soft limit and a hard limit, respectively. The bin sizes are then optimized such that the uncertainty in the farm power production estimate is limited to the specified values. The normalized standard error of the farm power per bin is used to quantify uncertainty. In essence, increasing the bin size leads to more data points falling within a certain wind bin, causing the normalized standard error to drop below a certain limit. Nevertheless, using a too large wind direction bin size may obscure the full potential of AWC, so this parameter must be chosen carefully. It is recommended to maintain the wind speed bin to 1 m/s and start with wind direction bins of 1 degree, increasing until desired uncertainty is reached.

The final data will be distributed over bins of varying size. This is to be expected due to the non-uniform wind speed and direction distribution. In other words, for certain wind directions where more data is available it is expected that the bins are thinner and for wind directions where few measurements exists the opposite. This can be seen in Figure 4, where the binning procedure using SCADA data from wind farm Anholt is used[1]. A maximum error of 0.05 and a desired one of 0.02 were chosen. The wind sector near 150 degrees is missing due to the lack of data around these wind directions.

1 *As there is no AWC operation in the dataset from Anholt, the data is simply divided into two data sets for testing purposes, data set 1 and data set 2.*

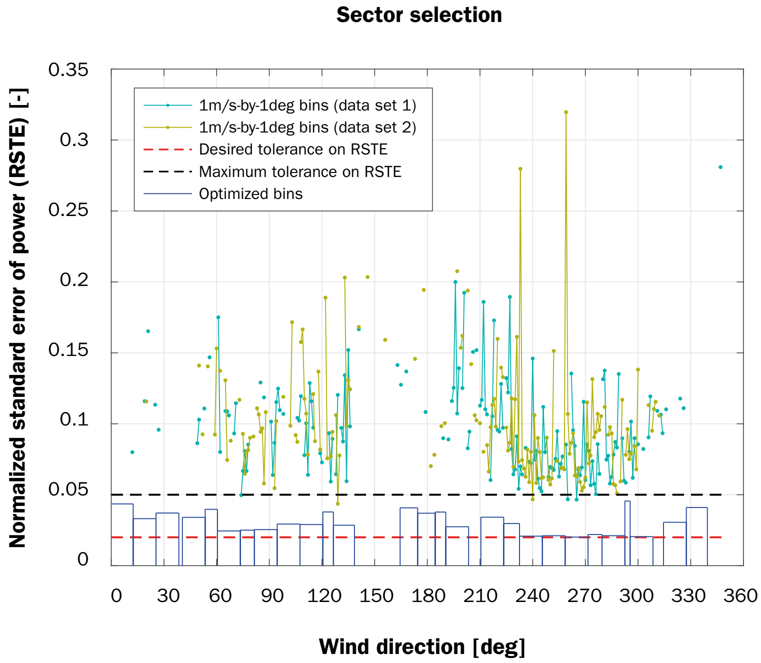

Figure 4 *Final result of binning procedure. Notice the bins of varying size, the initial normalised standard errors for both data sets (1 and 2, representing the nominal 1 and nominal 2 data sets), the hard (maximum) and soft (desirable) uncertainty, represented as black and red lines, respectively (Kanev, 2020).*

In each of the wind direction bins it is possible to compare the wind farm power curves for both nominal and AWC operation, along with the 95% confidence intervals. This is represented in Figure 5, where it can be observed that both curves for the two data sets, blue and red, fall almost on top of each other. This is expected, as they are both reflecting the same time of operation (normal, not AWC). For AWC operation, it is expected that the curve lays distinguishably above of the normal operation for certain wind sectors.

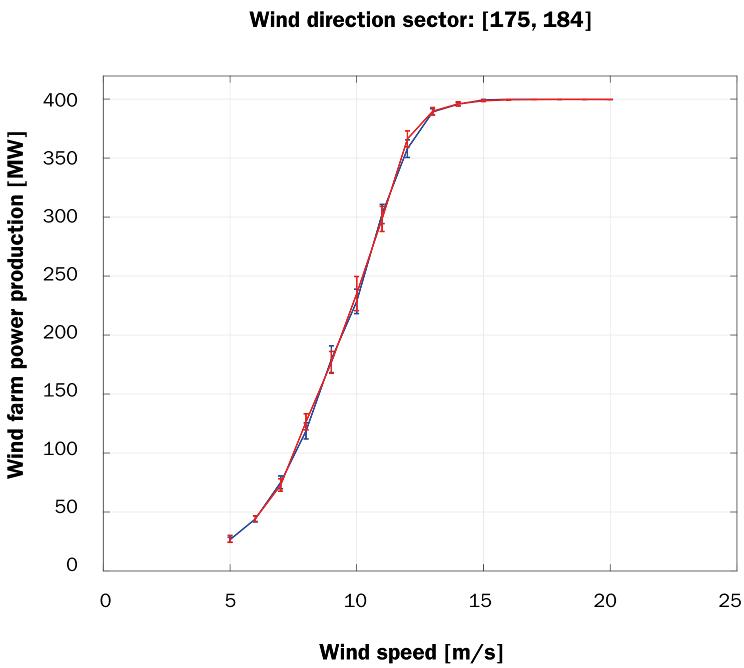

Figure 5 *Power curves for Anholt wind farm, wind direction sector comprised between 175 and 184 degrees. Data set 1 is represented in red and data set 2 is represented in blue (Kanev, 2020).*

E. CALCULATING POWER RATIO

How to calculate the relative power gain within each bin and on a yearly basis?

The fifth step quantifies the power gain for each of the bins and computes the final gain in Annual Energy Production (AEP) terms.

(Motivation) The final goal is to have an estimation of the AEP gain by using AWC. With such goal in mind, the power ratio between the two data sets is computed and the AEP is estimated based on the wind speed and wind direction distribution.

The first step encompasses the calculation of the power ratio statistics, i.e., the power ratio mean value per wind sector and the corresponding 95% confidence interval. For this, the wind farm power production statistics are used. It is often the case that within a certain bin there are (turbine) records representing rejected data, and completely filtering such time instants would yield a very limited dataset for the final analysis. For that reason, the methodology calculates the statistics per wind turbine first within the bin, and only then the statistics for wind farm power within the bin. Subsequently, the mean power ratio is computed for every wind sector. An example is depicted in Figure 6 for Anholt wind farm, where the mean values are calculated over the wind speeds up to 11 m/s to guarantee that the power ratio analysis is in the region of primary interest (below rated wind speed), and does not get biased by above rated operation of the wind farm. It can be further seen that for most sectors the mean power ratio lies within just 2% from the expected value of 1, with an uncertainty of about ± 3.5%.

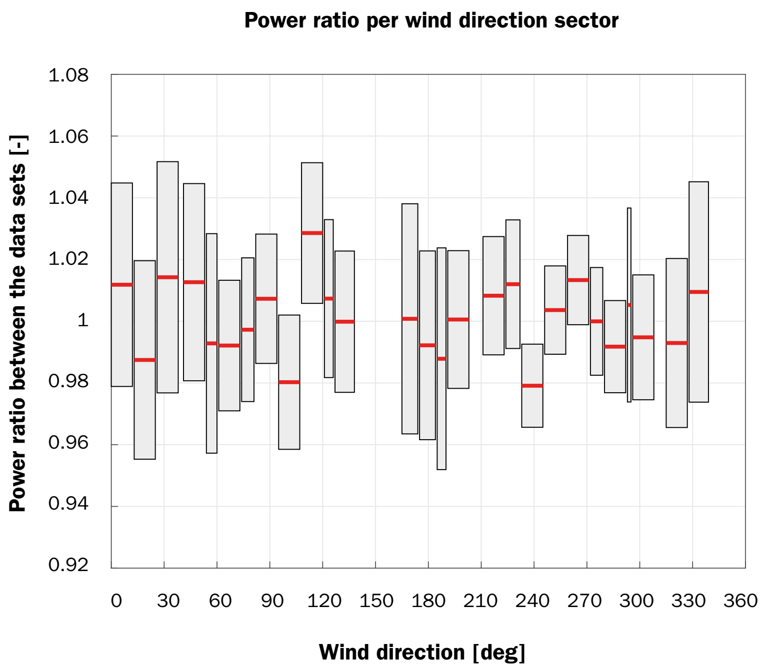

Figure 6 *Power ratio per wind direction sector for the Anholt wind farm: mean value (red) and 95% confidence interval (grey bars) (Kanev, 2020).*

The second step involves calculating the weighted average power production, where the frequency distribution per wind speed and direction bin is required. This can be achieved in two ways: either by providing a site-specific wind speed and wind direction probability density functions or, alternatively, by making use of the actual number of records within each bin to directly construct the frequency distribution using the measurement data from the AWC campaign. Using the one or the other, for each wind bin a weight α_b between 0 and 1 is computed, such that the sum of all weights for all bins equals 1. The weight represents the probability the wind conditions fall within wind bin *b*, and should be representative for both data sets.

For Anholt wind farm, the estimated mean value of the weighted average wind farm power ratio was 1.0006 with 95% confidence interval of ± 0.00166 around the mean value. For Westermost Rough wind farm, the estimated annual power ratio was 1.0016 with 95% confidence intervals of ± 0.0024 around the mean value *(Kanev, 2020)*. Both estimated AEP ratios are close to 1, as would be expected using the testing data sets without an AWC campaign. The differences in the two can be partly explained by the amount of data used for the final analysis: for Anholt, data rejection in the filtering process was approximately 50%, leading to 9 months of data in each dataset *(Kanev, 2020)*. On the other hand, for Westermost Rough, the percentage of data rejected was 64%, leaving 6.5 months of data in each set, which may lead to higher uncertainties in the overall estimation. The results are naturally dependent on the options specified by the user, such as the maximum allowable standard deviation in the consensus wind speed and direction, the maximum wind sector bin width and the maximum and desirable standard errors in the binning process.

The example for Westermost Rough in *(Kanev, 2020)* sets as maximum standard deviation of consensus wind speed 2.5 m/s and for wind direction 10 degrees. In addition, the maximum sector width is set to 12 degrees. By adopting a more conservative approach and setting the three values to 1 m/s, 8 degrees and 10 degrees, the estimated AEP ratio is 1.00090 ± 0.0027, showing that the results are sensitive to the options used and a proper evaluation is in need. The final result of data binning is shown in Figure 7.

A more insightful visualisation is the power ratio per wind speed and direction bin. This is depicted in Figure 8. For a great majority of the quadrants shown, the power ratio is close to 1. For others, especially between 90 and 160 degrees and below 6 meters per second, power ratios are different from one bin to another. This is due to the low data availability for these wind bins, as Figure 9 points out (for this heatmap equally spaced wind direction sectors of 10 degrees were chosen).

The low data availability between 90 and 160 degrees leads to increased uncertainties as well. The normalised standard error is notoriously higher in these regions, as Figure 6 exhibits, by a factor of 1.5 to 2 times, when compared to wind directions where more data is available, such as between 180 and 300 degrees wind direction bins.

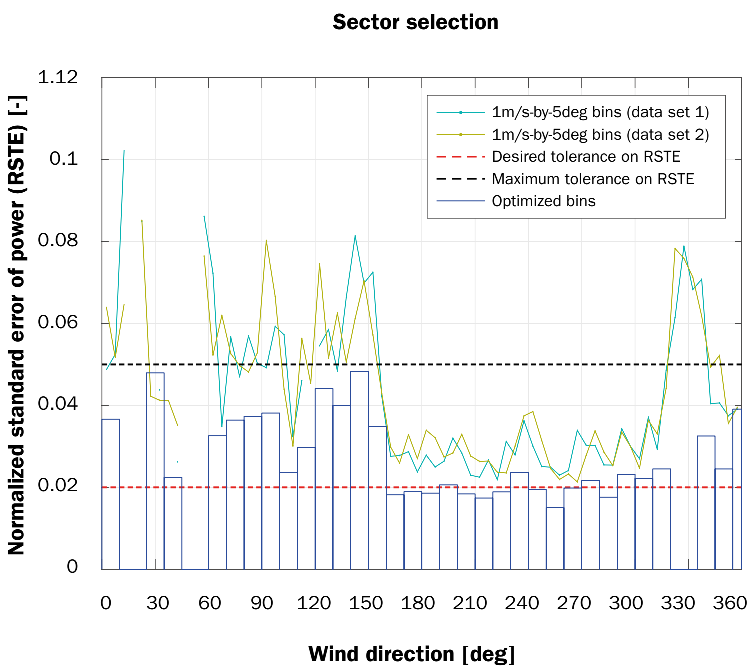

Figure 7 *Final result of binning procedure using a more conservative approach (higher quality standards) for Westermost Rough wind farm. Bin widths constrained between 5 and 10 degrees.*

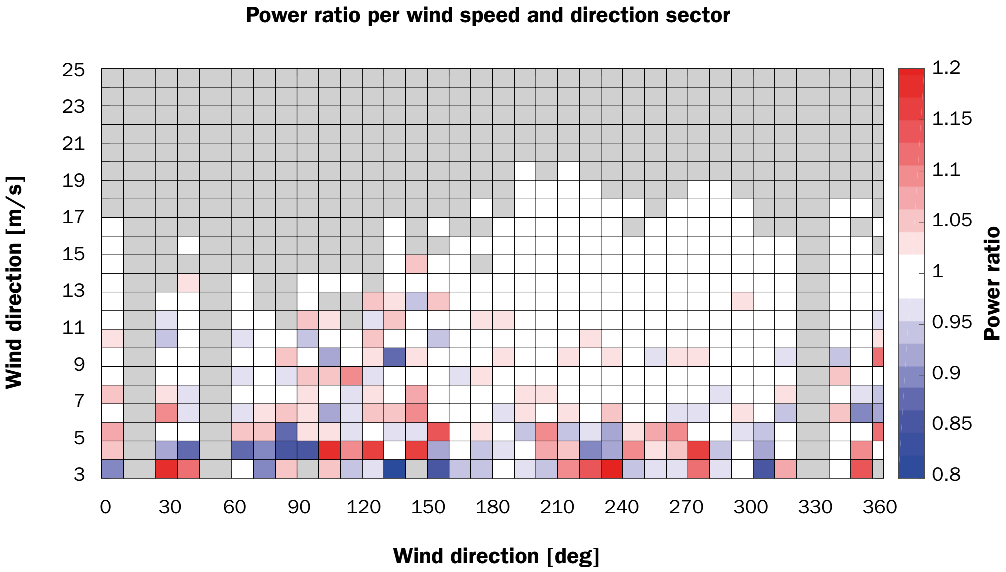

Figure 8 *Power ratio per wind speed and direction bin. White quadrants represent a power ratio of 1, red quadrants a power ratio higher than 1 and blue quadrants a power ratio lower than 1. Grey quadrants represent unavailable data (either inexistent or not sufficient in binning process).*

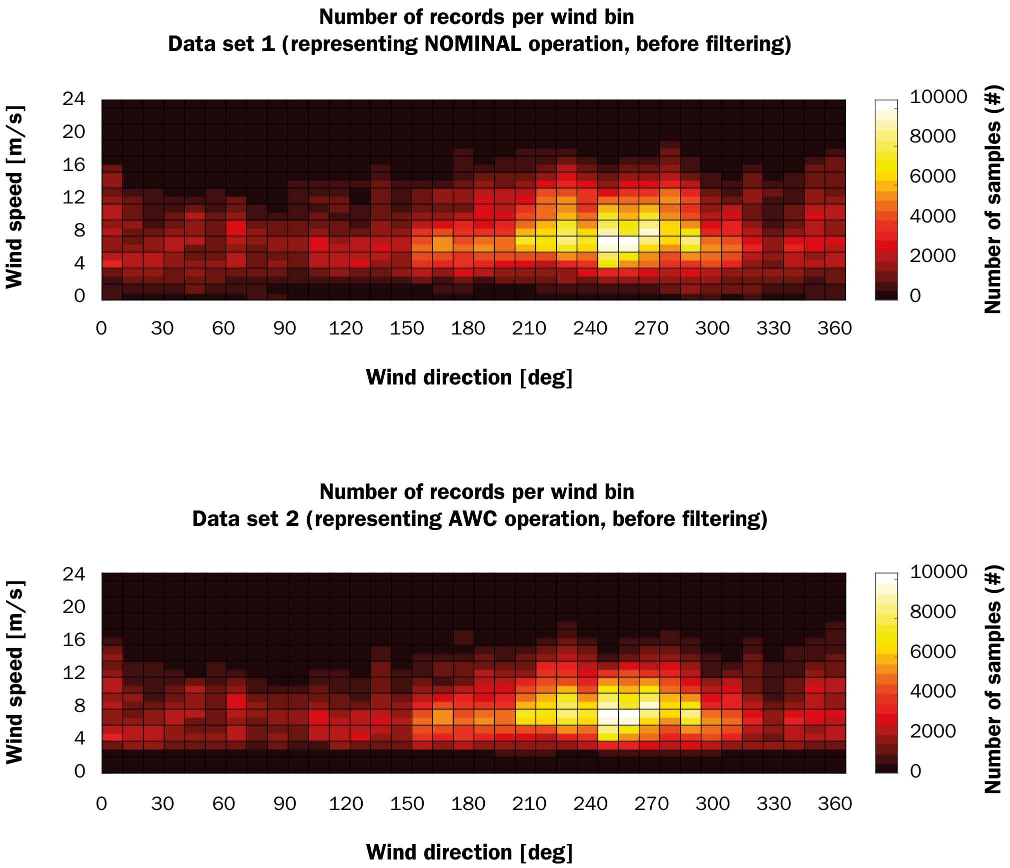

Figure 9 *Number of data records per each wind speed and wind direction bin for SCADA data from Westermost Rough, before filtering procedure.*

F. QUANTIFYING UNCERTAINTY

How to quantify the uncertainty on the relative power increase?

In the sixth step, the uncertainties of the final power gain, per wind speed and wind direction bin, are properly quantified at the farm level, including the A and B category uncertainties.

(Motivation) An uncertainty analysis aligned with the IEC 61400-12-1:2013 is performed. There, the A and B category uncertainty components are firstly developed separately for the NTF and the nacelle power curve, as defined in *(International Eletrotechnical Comission, 2013)*.

Within the context of the AWC validation method, the uncertainty components related to the process of determination of the WSTF and WDTF are listed, then those affecting the calculation of the consensus wind speed and wind direction and finally those for the wind farm power production. For more details on the rationale for the values chosen and mathematical background, the reader is referred to *(Kanev, 2020)*.

The A and B category uncertainties along with the combined uncertainty are first calculated per bin for each of the two data sets, as exemplified in Figure 10. The A category uncertainty is calculated based on the stochasticity of the measured signals. The B category uncertainties have been adopted from examples in Annex G in the IEC61400-12-2:2013 standard for demonstration purposes. The later are related with calibration procedures, operational characteristics, mounting effects, the data acquisition system, etc. Clearly, the overall uncertainty is mostly dominated by the B category uncertainty *(Kanev, 2020)*.

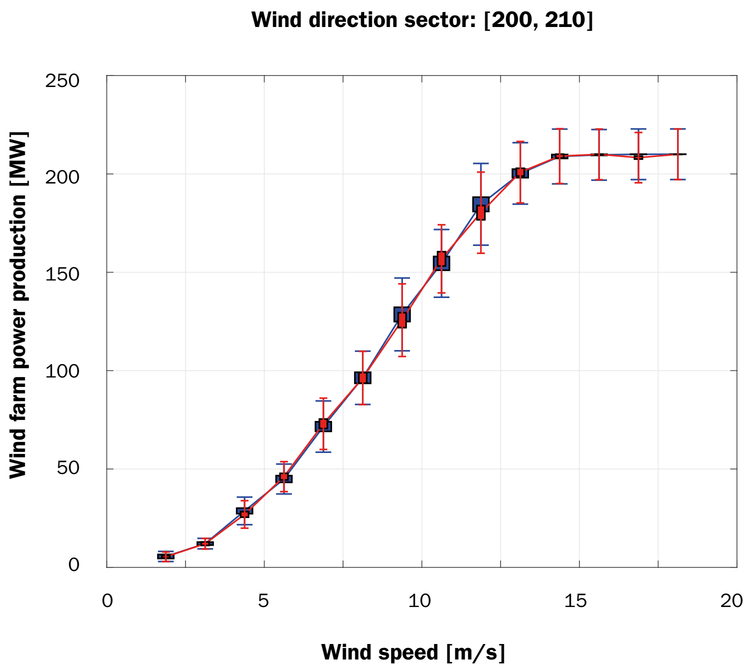

Figure 10 *Uncertainty on the power curves for the Westermost Rough wind farm for wind direction bin between 200 and 210 degrees. The blue and red colours corresponds to the two data sets. The thick boxes represent the A category uncertainty. The line segments represent the combined uncertainties (A and B).*

The overall uncertainty is then computed for the different wind sectors and is represented in Figure 11 for Westermost Rough (weighted average calculated using only wind speed up to 13 m/s). It is also evident in Figure 11 that the category B uncertainties are dominant in the power ratio. On average, the uncertainty on the power ratio in nearly 20% *(Kanev, 2020)*.

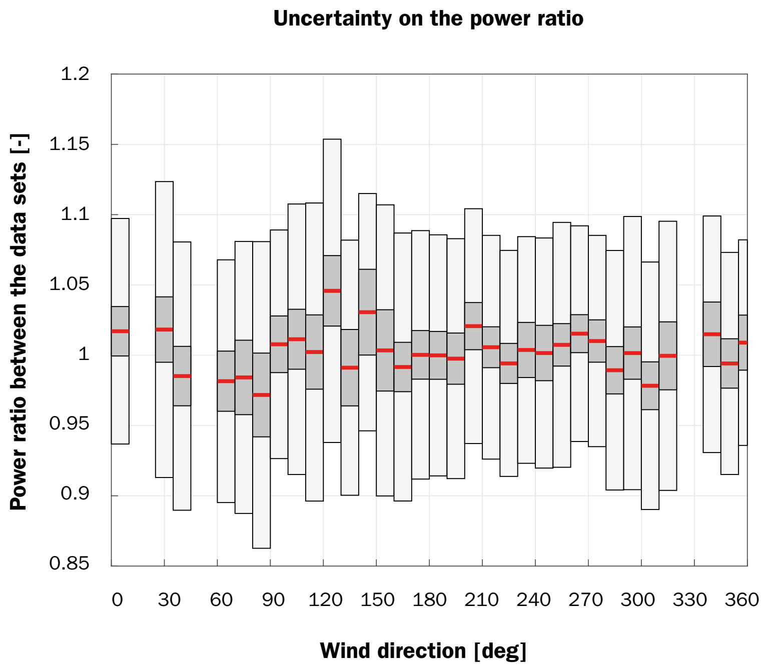

Figure 11 *Uncertainty on the power ratio per wind direction sector for Westermost Rough wind farm. The dark shaded bars represent the A category uncertainty, the light shaded bars represent the combined uncertainties (A and B). The red lines represent the mean values of the power ratio.*

G. ASSESSING IMPROVED PERFORMANCE AT THE TURBINE LEVEL

How to quantify the benefit of AWC at the turbine level?

In the seventh and final step, a dashboard per wind turbine is created to assess and visualise the improvement from AWC operation at the turbine level.

(Motivation) At this point, the annual weighted average power ratio, based on the wind speed and direction distribution has already been calculated. This figure serves as an estimate of the AEP expected increase, the result of most interest. Nevertheless, it is also possible and of high interest to evaluate the improved performance at the turbine level.

An example of such dashboard for turbine number 1 in Westermost Rough is represented in Figure 12. The first row shows the weighted average power ratio per each wind direction sector. Wind sectors of 5 degrees were here used for simplicity purposes and these can be easily changed. These were calculated based on the average power ratio for each wind speed bin (represented in the below plot) and the total number of records for both data sets, depicted in the last plot (after the filtering procedure and actually used for the final analysis). Only data record between 6 and 14 m/s were used in order to avoid biasing results with too low and too high wind speeds.

The majority of the power ratios over the wind sectors is 1. This can be clearly seen in wind directions comprised between 120 and 315 degrees, for both the weighted average and per wind speed bin. This is to be expected as there is no AWC operation. However , a power ratio of 1.2 is seen between 15 and 20 degrees , which is not expected. This is thought to be an artifact and not a representative result. The particularly high standard deviation in the power ratio, reaching 1.4 in the wind speed bin between 9 and 10 meters per second, is thought to be the cause. The representation of the standard deviation per wind bin, along with the total number of points used, serves to put the result into a better perspective.

Below, the wind farm layout is represented, and a red circle encapsulates the turbine being analysed, along with a sketch of the expected wake interaction between farms based on a simplified wake expansion model. It is then possible to relate the position of the turbine and the magnitude of wake overlap with the weighted power ratio per wind direction. For wind directions where wake overlap is expected to be more severe weighted power ratios should yield higher values, a consequence of AWC operation.

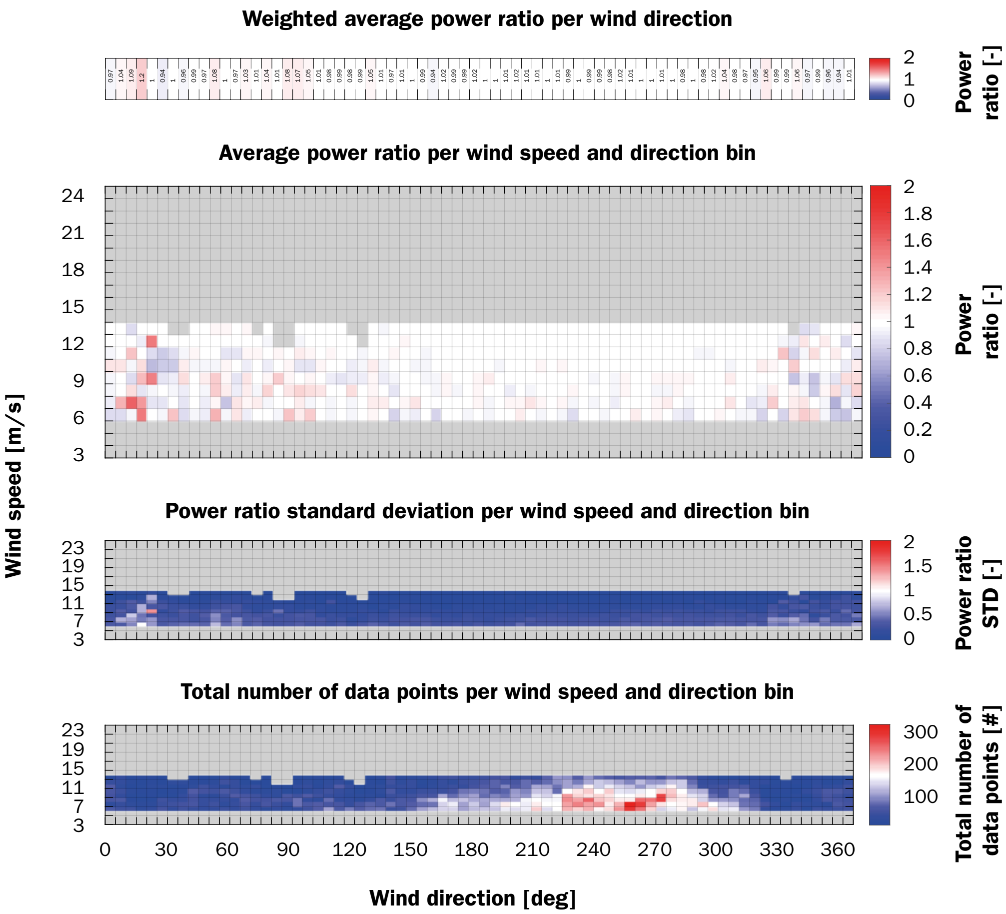

Figure 12 *Dashboard for assessing benefits of AWC operation at the turbine level. The first plot show the weighted average power ratio per wind direction sector. The second (below) plot depicts the power ratio for the turbine being analysed for the various wind speed and direction bins. The third plot show the standard deviation for the same bins and the fourth plot the total number of data points from both data sets used for the final analysis (the last two to put the results into more context).*

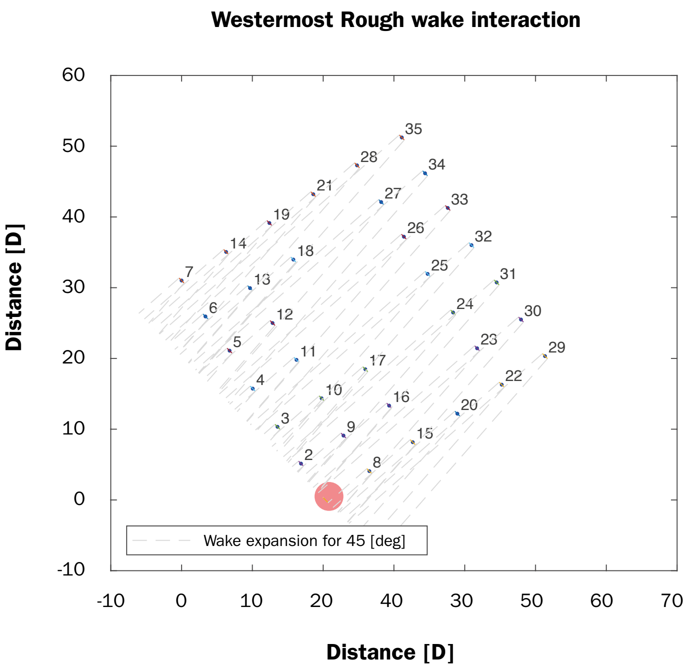

Figure 13 *Representation of the wind farm, along with wake interactions using a simplified wake expansion model. Turbine being analyzed is encircled in red.*

FUTURE WORK

At the moment this document was created the validation methodology was being applied to the data from the AWC campaign from wind farm Sandbank. Fine tuning of the developed methodology here reported in light of the data set from the AWC pilot project campaign is work in progress. Future work shall focus on further analyzing more data from offshore campaigns as AWC begins to gain traction, improve upon AWC validation techniques and implementation methodologies and research AWC for floating wind farms.

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