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1. Introduction

The growing size of wind turbines and wind farms in the offshore environment, eventually occupying tens of kilometers and extending beyond 200 m in height, has challenged traditional wind farm models to incorporate larger atmospheric scales with greater influence from the full extent of the atmospheric boundary layer (ABL). The modeling system is subject to variability from mesoscale weather phenomena like land-sea transitions or farm-farm effects that produce horizontal gradients in the wind resource, as well as phenomena like low-level jets, gravity waves, etc, that modify the turbulence structure of the ABL as it interacts with the wind farm [1][2]. The transition to multi-scale wind farm modeling requires a systematic methodology that allows determining the relative importance of these effects in wind farm performance and the predictive capacity of models [3]. This is especially important for offshore wind developers that face significant financial and operational costs due to uncertainties in wind resource assessment [4]. Understanding how these uncertainties originate from wind farm design tools is of fundamental importance to mitigate these losses.

The *OWA Wake Modeling Challenge* is an Offshore Wind Accelerator (OWA) project that aims to improve confidence in wake models in the prediction of array efficiency. Model developers and end-users were invited to participate in a benchmarking exercise along a suite of validation datasets that spans a wide range of operational conditions in terms of wind farm topology and wind climate characteristics [5]. In the absence of free-stream meteorological observations, a meso-wake modeling framework is proposed where the background wind resource conditions are defined from reference mesoscale simulations based on the New European Wind Atlas (NEWA) model configuration of the Weather Research and Forecasting (WRF) model [6][7][8].

The challenge consisted in two phases: a blind test phase for code-to-code verification of model spread, where simulations where entirely driven by mesoscale input data; and a calibration phase, where mesoscale bias was analyzed to correct input data and allow a fairer assessment of engineering wake models against observations.

This paper summarizes the results of this challenge and builds on previous research towards the definition of a model evaluation methodology for array efficiency prediction that leverages data from operational wind farms [9][10][11][12]. An open-source repository of evaluation scripts is made available to engage with current and prospect benchmark participants through a transparent evaluation process and to promote further uptake in future research projects as more data becomes available [5]. The reader is encouraged to browse through the open-source repository and explore more detailed results for each of the sites.

2. Validation Scope and Objectives

The primary objective of the OWA challenge is to understand the limitations of engineering wake models used by industry for the prediction of array efficiency in large offshore wind farms for energy yield assessment. Array efficiency η for a wind farm of n_{wt} turbines is defined as the ratio of the net power output to the available gross power:

$$\eta = \frac{\sum_{i=1}^{N_t} P_i}{\sum_{i=1}^{n_{wt}} P(S_i)} \tag{1}$$

where P_i and S_i are the power and free-stream wind speed at turbine position i. Hence, the wind farm power loss is $1 - \eta$. Note that the gross power is defined in terms of the theoretical power curve, $P(S_i)$, at each turbine position as if it were operating in isolation. This is in contrast to previous validation studies that assumed uniform free-stream conditions for the entire wind farm.

In effect, the validation strategy addresses engineering wake models, developed under the assumption of surface-layer inflow conditions that are horizontally homogeneous and steady-state. Large wind farms are subject to heterogeneous inflow due to coastal gradients, wakes from neighboring wind farms and other mesoscale phenomena. The interaction of the ABL with the wind farm canopy includes different processes from the upstream blockage of the flow [13], to the generation of an internal boundary-layer that, in very large arrays, results in a fully developed wind farm boundary layer where array efficiency becomes relatively constant (deep-array effect) [12]. Under stable conditions the ABL height is compressed to a few hundred meters and a low-level jet forms. In the presence of large wind farms, this low-turbulence regime generates long-lasting wakes and introduces significant reductions in the array efficiency compared to neutral or unstable conditions [14][15][16].

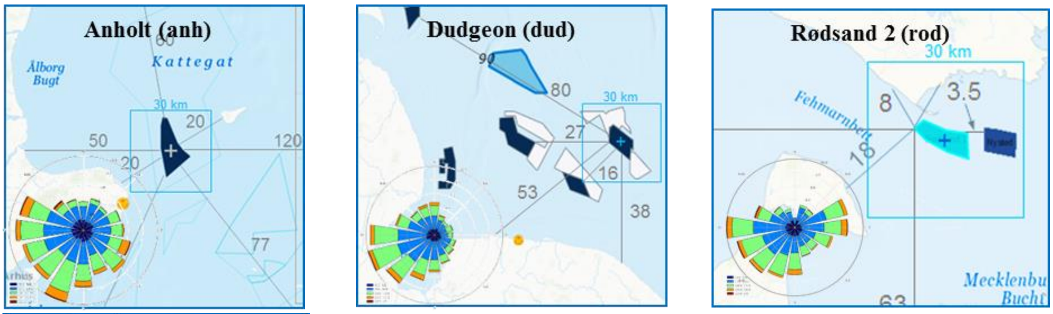
Since the intended use of the models focuses on energy yield assessment, we are interested in the validation of long-term averaged conditions, categorized by wind direction, wind speed and stability classes. Hence, the validation metrics will be based on bin-averaged conditions and not on the analysis of time series in connection to specific weather conditions.

3. Validation Sites

The validation consists of 5 sites in different Northern European wind climates (Table 1, Figure 1).

Table 1: Wind farm characteristics, geographical location and evaluation periods.

Wind Farm	Data Provider	LON (°)	LAT (°)	From	To	P_{total} (MW)	N_t	P_{rated} (MW)	D (m)	z_{hub} (m)
Anholt	Ørsted	11.2	56.6	Jan-13	Jun-15	399.6	111	3.6	120	82
Dudgeon	Equinor	1.38	53.26	Dec-17	Nov-18	402	67	6	154	110
Rødsand 2	EON	11.46	54.57	Feb-13	Jun-14	207	90	2.3	82,4	68,5
Westermost Rough	Ørsted	0.15	53.80	Jan-16	Dec-17	210	35	6	154	106
Ormonde	Vattenfall	-3.44	54.09	Jan-12	feb-19	150	30	5	126	100



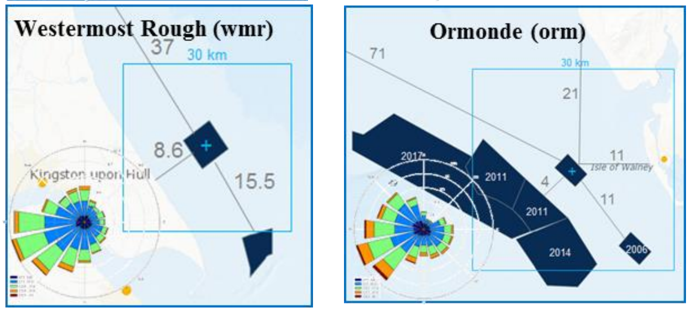


Figure 1. Offshore wind farms participating in the OWA challenge. Distances indicated in kilometres. Windroses for the evaluation period of each site as per Table 1 (basemaps from 4Coffshore.com as of October 2019).

Anholt is a large wind farm extending for 22 km in the N-S direction with important coastal gradients from the West. Peña et al [10] analyzed the Anholt wind farm and introduced the idea of using mesoscale input data with engineering wake models. The global bias in array efficiency was below 2% but with deviations at turbine level that could be higher than 20%. van der Laan et al [17] also showed the challenges of simulating coastal gradients with a CFD model for such a large wind farm when using idealized inflow boundary conditions.

Westermost Rough runs in parallel to the shoreline which is affecting the prevailing wind direction from SW. Nygaard and Newcombe [18] presented dual-Doppler radar measurements of the flow along this direction noticing how the wake from the wind farm persist beyond the range of the measurements 17 km downstream. They also presented results with engineering models highlighting their limitations to incorporate the coastal gradient effect.

All the other sites are affected by wake effects from neighbor wind farms, situated at distances from 3.5 to 27 km. Rødsand 2 has been also subject of study in previous wake projects, e.g. [9][11], especially in regards to the interaction with the Nysted wind farm to the East. Nygaard presents how the directional array efficiency of Nysted is reduced by up to 20% by the presence of Rødsand 2 in this direction with an increase in turbulence intensity of a few percent [9].

4. Wake Models and Validation Framework

4.1. Meso-Wake Framework

A mesoscale-to-wake modelling framework is established whereby mesoscale simulations are provided as input data for the modellers to interpret in connection to their wake models. The Weather Research and Forecasting (WRF) model configuration used in the New European Wind Atlas (NEWA) is adopted as a reference for mesoscale modeling [5][7], adding the Fitch wind farm parameterization to include farm-farm wake effects at a horizontal resolution of 3 km [19][20]. According to [8], the bias in the mean wind speed at 100 m is below 3% in offshore conditions. A 3% bias turns into 9% gross power bias through the power-curve relationship.

4.2. Wake Models

Eleven participants registered in the challenge covering a large variety of engineering wake models present in commercial as well as research codes. The results presented here come from six participants that submitted simulations for all the sites to carry out a multi-site assessment (Table 2).

All participants in this group adopted a time-series approach where each hourly interval is assumed stationary. We use hourly data and not 10-min data to account for the time lag for wind conditions to propagate across the wind farm. In effect, for a 22-km long farm like Anholt, it takes 40 min for air moving at 9 m/s to traverse the wind farm from North to South.

Table 2: Wake models (*ref* and *wt* denote homogeneous and heterogeneous inflow)

ID	Participant	Wake Models (Code)	Input
0	CENER	Porté-Agel, Jensen, Multi-zone (FLORIS)	*ref*
1	ProPlanEn	WakeBlaster	*wt*
2	TU-Delft	PARK83, Bastankah&Porté-Agel (eWakeLab)	*wt*
5	EMD	PARK2 (windPRO)	*wt*
7	IFPEN	Ishihara&Qian, Bastankah/Ishihara&Qian, super-Gaussian/Ishihara&Qian (FarmShadow)	*ref*
8	EDF Renewables	PARK, PARK2 (windPRO)	*wt*
-	Ensemble	1+2+5+8	*wt*

Time series of mesoscale wind conditions were provided for each turbine (denoted *wt*) and for the average of all turbines (*ref*) to accommodate the needs from the models to use heterogeneous or homogeneous inflow conditions respectively. These homogeneous inflow conditions are assumed at the wind farm centroid (coordinates in Table 1) and are used as a reference virtual mast to categorize wind conditions in terms of wind direction, wind speed (S_{ref}) and stability.

Then, in a meso-wake framework the predicted power P_i at turbine position i can be defined as:

$$P_i = P_{ref,i} A_{S,i} A_{M,i} = P_{wt,i} A_{M,i} \tag{2}$$

where $A_{S,i}$ and $A_{M,i}$ are correction factors to account for changes in power within the array, due to horizontal wind speed gradients, and mesoscale bias respectively. Assuming power-curve relationships between power and wind speed:

$$A_{S,i} = \frac{P_i}{P_{ref}} \approx \left(\frac{S_i}{S_{ref}}\right)^3 \tag{3}$$

$$A_{M,i} = \frac{P_{obsfree,i}}{P(S_i)} \approx \left(\frac{S_{obsfree,i}}{S_i}\right)^3 \tag{4}$$

where S_i is the background mesoscale wind speed and $S_{obsfree,i}$ is the observed equivalent free-stream wind speed, which is obtained from the observed power $P_{obsfree,i}$ at wake-free turbines though the inverse of the power curve. Since $S_{obsfree,i}$ is deduced from the power of the free-stream turbines, we assume that potential effects of upstream wind farm induction are included in $A_{M,I}$, which would correct for both mesoscale and induction or blockage. According to [13] wind farm induction effects can result in up to 4% overestimation of array efficiency in engineering wake model when they operate at the maximum thrust coefficient. Hence, it is worth removing this effect in the assessment of array efficiency so we can be sure that it is only related to wake losses.

4.2.1. FLORIS (CENER)

FLOw Redirection and Induction in Steady State (FLORIS) is an open-source set of controls and optimization tools used for wind farm control, developed by NREL and Delft University of Technology [21]. The 0.4.0 version was used in this study to test the application of the following wake models in array efficiency prediction: N.O. Jensen [22], Gaussian [23][24][25] and Multi-zone [26]. All models where run in neutral conditions only. A wake decay coefficient of 0.05 was used in Jensen. The Gaussian model uses these set of parameters: *alpha* = 0.58, *beta* = 0.077, *ka* = 0.17 and *kb* = 0.06. The Multi-zone model is a modification of the Jensen model, which splits the wake into three different wake zones: near-wake zone, far-wake zone, and the mixing-wake zone. It uses the following parameters: *aU* = 11.7, *bU* = 0.72, *mU* = [0.47,1.28,5.5] and *me* = [-0.5, 0.3, 1]. Time series of power production at each turbine are calculated for each time step based on the centroid conditions.

4.2.2. Wakeblaster (PPE)

WakeBlaster is a parabolic three-dimensional RANS solver, developed by ProPlanEn (PPE) [27][28]. It is a “field model” that solves the waked flow field for multiple turbines at once rather than a singleturbine model to eliminate the need for an empirical wake superposition model. It belongs to a class of very fast (a few core seconds per flow case) mid-fidelity models which are designed for industrial application in wind farm design, operation and control. WakeBlaster is driven by the output of a less detailed external (microscale or mesoscale) flow model.

The model solves the RANS equations on a three-dimensional structured grid, with a 0.1D resolution in all three directions. It uses an eddy viscosity turbulence closure that is parameterized by using the local shear, time-lagged turbulence development, and stability correction for ambient shear and turbulence decay. The model prescribes a Gaussian momentum deficit at the end of the near wake. The WakeBlaster model has been verified, calibrated and validated with a large volume of SCADA data from multiple land-based and offshore wind farms.

4.2.3. eWakLab (TUD)

eWakeLab is an in-house engineering wake modelling toolbox (written in MATLAB™) which can ingest spatio-temporally varying hub-height wind speeds from a mesoscale model or a reanalysis dataset. It contains a few well-known wake parameterizations (e.g., [22], [24]) and there is a plan to include several newly proposed ones from the literature (e.g., [29]). eWakeLab uses a UTM coordinate system-based grid with a user-specified grid-size (typically 100 m) and requires a prescription for the maximum length of wakes (typically assumed to be 50 times the rotor diameter). One of the salient features of eWakeLab is that, for a given time instant and a location, it combines the wakes of all the upstream turbines in an iterative manner. During each iteration, effective wake deficits are updated, and in turn, the thrust coefficients of all the affected turbines are properly adjusted based on the localized wind speeds. eWakeLab supports several types of wake superposition (e.g., linear, quadratic). We would like to note that eWakeLab will be released in the public domain in the near future; currently, it is available upon request from S. Basu.

4.2.4. windPRO (EMD)

The basis is the DTU developed PARK2 [30], a refined version of the original N.O. Jensen PARK model [22]. The model uses the WakeDecay Constant (*WDC*) and turbine C_t values to calculate the wind speed deficit behind the rotor. The combination of the deficits from more wake turbines is the major change in PARK2, where in the original this was empirically based, now it is formulated physically with new equations. The *WDC* can be set by time step based on turbulence intensity (*TI*) or stability. By converting stability (adding an offset), it is also possible to let this signal control WDC by time step from windPRO. EMD used $WDC = 0.8TI$ for offshore wind farm in the benchmark.

4.2.5. FarmShadow (IFPEN)

FarmShadow is an in-house, steady-state code developed at IFP Energies nouvelles. An aerodynamic library based on the IFPEN Blade Element Momentum (BEM) model (integrated in the hydro-aero-servo-elastic solver DeepLinesWind™ [31]) is coupled to a set of analytical wake models. When minimal information is available on the turbine, as it was the case here, the BEM model is replaced by an actuator disk method where only C_p and C_t tables are needed. The disk is discretized using several control points, on which velocities and turbulence intensities are evaluated, including the effect of upstream turbine wakes. Then, these quantities are averaged and used as an input to calculate the wake of a given wind turbine. Here, FarmShadow results are based on three velocity deficit models (Gaussian models of Bastankhah&Porté-Agel [24], Ishihara&Qian [32], and the super-Gaussian model of Blondel&Cathelain [33]) and the added turbulence model of Ishihara&Qian [32]. A linear superposition is assumed for both velocity deficit and turbulence intensities. In terms of inflow, FarmShadow is based on a horizontal uniform wind field with vertical wind shear based on power-law exponents. Ambient turbulence intensity is prescribed for the wake-added turbulence model. The coefficients of the models are not dependent of the atmosphere stability.

4.2.6. windPRO (EDF Renouvelables)

windPRO recommendations for offshore wind farm for the WDC dependency on *TI* were followed for PARK (*WDC* = 0.67*TI*) and for PARK2 (WDC = 0.8TI). Additionally, we also run PARK with a constant *WDC* of 0.038. When the wake decay is above 0.2 or below 0.01, it is fixed based on the *TI* at the centroid, where *TI* is calculated based on the mesoscale turbulent kinetic energy (TKE_{ref}).

$$TI_{ref} = \frac{1}{S_{ref}} \sqrt{\frac{TKE_{ref}}{0.945}} \tag{5}$$

5. Model Evaluation Methodology

5.1. Validation Metrics

The assessment is based on bin-averages of array efficiency for S_{ref} = 9±1 m/s, where the thrust coefficient is at its maximum generating the strongest wake effects, per 30º-width wind direction sector and stability class. Stability is based on the simulated Obukhov length L_{ref} for: unstable ($-0.2 < z/L_{ref} < -0.02$), neutral ($-0.02 < z/L_{ref} < 0.02$) and stable ($0.02 < z/L_{ref} < 0.2$) conditions, with z = 10 m.

Performance is measured in terms of the *BIAS* and mean absolute error (*MAE*):

$$BIAS = \eta_{sim} - \eta_{bench} \tag{6}$$

$$MAE = |\eta_{sim} - \eta_{bench}| \tag{7}$$

where the benchmark data come from either the observations or the ensemble (blind test). The metrics are calculated for each turbine and wind farm per bin and then weighted-averaged with the wind climate distribution to calculate integrated quantities. To limit the influence from bins with poor statistical significance, only bins with more than 25 samples are used to compute integrated quantities.

5.2. Validation Data

Operational data from offshore wind farms provided by OWA partners are filtered and processed in order to generate the validation datasets. To this end, the data is first standardized to a common format and is subject to a quality-check process that will essentially determine if the power from a wind turbine at any given time is working in nominal conditions, i.e. when the power is close to that predicted by the theoretical power curve at the operational nacelle anemometer wind speed. It is under these conditions that wake models are used during the pre-construction phase of a wind farm. The boundaries of nominal conditions are defined by a symmetrical horizontal displacement about the theoretical power curve that end up excluding around 20% of the data points as outliers.

To improve the statistical representativeness of the validation data, non-nominal turbines are identified and corrected to nominal conditions. A gap-filling methodology based on machine learning builds a predictive model for each turbine using data from cluster turbines whose response is highly correlated with the target turbine. A sensitivity analysis was performed to select the most appropriate input data and regression model. The best results were obtained by using nacelle wind speeds as inputs to a regression trees model. Nevertheless, hourly data retained for validation include less than 10% of gap-filled turbines in every time stamp to minimize the impact from the corrected data. This threshold allows keeping between 50 and 70% of the data, which corresponds to 8-10% within the validation range of 8 to 10 m/s. At this threshold or above the impact on the overall bias was less than 0.5%.

5.3. Input Data

Generic power and thrust curves were kindly provided by EMD. Following the same strategy that was adopted in the EERA-DTOC project [35], two sets of input data are generated:

- ***Control***: Free of wake effects, to characterize the background wind resource.
- ***Wakes***: Includes neighbor wind farms but not the target wind farm, to characterize inflow conditions for microscale wake modeling.

This allows quantifying the impact of mesoscale wake effects on the wind resource and provides modelers with the possibility of simulating the target wind farm alone (*wakes* approach) or consider the cluster of wind farms all in the same microscale simulation (*ctrl* approach).

As mentioned in Section 4, it is necessary to introduce a correction in the input data in order to limit the influence of the mesoscale bias in the assessment of wake models. To this end, a ray-casting algorithm is used to identify turbines in the periphery that can be considered free of wake effects. This is so when they do not have any turbine upstream within a 45º sector centered at the reference wind direction. Free-stream power is propagated into interior turbines using nearest-neighbor interpolation from the boundary free-stream turbines. Then, time-series of the observed free-stream wind speeds for each turbine can be used to run simulations with the least influence of mesoscale bias. Note that we still use mesoscale wind direction and stability to define the reference conditions.

An alternative when observational data cannot be shared is to produce bin-averaged correction factors $A_{M,i}$ that are applied to the mesoscale time series to scale the wind resource to the same level of the observations. For instance, Figure 2 shows the variability within the wind farm for one bin and the integrated global correction for Dudgeon, which results in an overall correction of 0,892. This factor has been verified with mast measurements at a 90-m mast at Race Bank (2006-2008), 35 km West from Dudgeon, arriving to a similar overestimation of the wind resource.

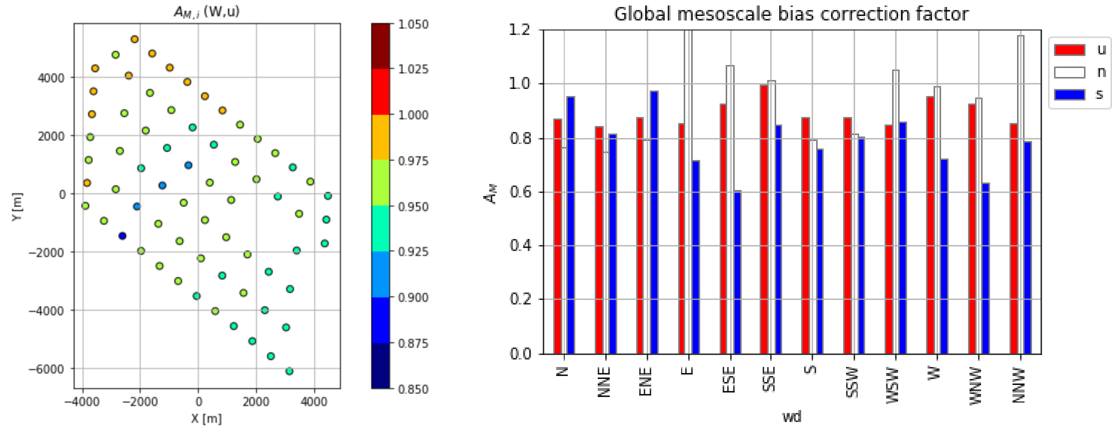


Figure 2: Mesoscale (*wakes*) bias correction at Dudgeon for (W,u) bin (left) and integrated for all the wind farm per wind direction and stability bin (right).

This method to define free-stream wind speed from SCADA is also applied to the simulations in order to have a consistent definition of the gross power in equation (1). This will impose an array efficiency equal to one to the free-stream turbines making the assessment less dependent on input data.

6. Results

6.1. Blind Test Phase

The first phase of the benchmarking process follows a blind test approach where participants do not have access to observational data. Instead, an ensemble, based on the simulations that include heterogeneous inflow and stability (Table 2), is defined to quantify deviations with respect to a benchmark model. The objective of this phase was to remove potential inconsistencies between the benchmark set-up and the interpretation of the modeller to identify outliers and reduce the spread of the simulations. The results showed reasonably good consistency among models, with the largest spread between models found in connection to large horizontal gradients and stable conditions.

6.2. Calibration Phase

Mesoscale corrected input data (*wakes-corr*) was provided to run a new set of simulations and compare with observations. In addition TU-Delft could also run simulations for Dudgeon and Ormonde wind farms using directly the free-stream wind speed generated from the SCADA data.

Figure 3 shows the spread of the overall metrics for each site. We observe a tendency towards negative BIAS in all sites but Dudgeon. This could be attributed to different factors, namely: underestimated turbulence intensity in mesoscale model simulations; streamwise gradients in the gross power not

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captured by the free-stream method and not resolved well by the mesoscale model; and turbine performance and local interaction effects not captured by models. Since we use the SCADA data in both the gross and the net power, we speculate that most turbine performance and local interaction effects will be cancelled out in the observations. Notice that, by using the same method to define the gross power in simulations than in observations we largely eliminate the dependency of array efficiency on the lateral wind resource gradients, making *ref* and *wf* models more comparable. At the same time, we are removing turbine performance and possible wind farm induction effects in the observations by having them included in both the gross and the net power. This assumption may not hold for interior turbines that could present different performance and may be affected by additional interaction effects that are not present in the free-stream turbines.

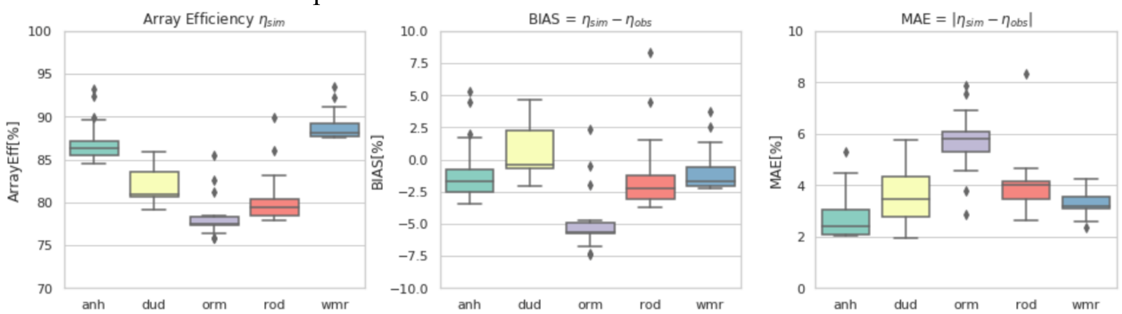

Figure 3: Overall performance for all sites and simulations (without mesoscale correction).

As expected, the largest errors are found in Ormonde, where a 3-km resolution mesoscale model is not detailed enough to solve the large wake effects from a large cluster of wind farms just 4 km upstream. In this particular case, the BIAS was cancelled out by simulating the cluster of wind farms at microscale. This was also the case in Rødsand 2 for the East sector. In this particular case we could see streamwise gradients increasing the gross power by more 20% in stable conditions. These gradients cannot be characterized correctly from SCADA data and, therefore, we should expect higher uncertainty. In general, we could see some dependency of array efficiency on the streamwise gradients that suggest that they affect the assessment of wake models.

Figure 4 shows the overall metrics for individual Dudgeon simulations categorized in terms of the input data. The ensemble was effective at decreasing the errors from the individual simulations in Dudgeon as well as in the other sites.

Using corrected inflow with models that assume homogeneous inflow (*ref*) does not affect array efficiency since the correction in the gross power is linearly transferred to the net power. In contrast, models based on heterogeneous inflow (*wt*) show a non-linear feedback. By comparing the results from TU-Delf using *wakes-corr* and *scada* inflow in both Dudgeon and Ormonde, it is noticed that the linear correction introduced in the gross power resulted in a negative bias of around 2% in array efficiency. Since this correction includes non-linear interaction effects, it would be necessary to iterate with the wake model to match the results that we obtain with the *scada* inflow.

The sensitivity of the results to the wake decay coefficient (K) shows how this parameter can be used to calibrate wake models provided we have removed first the input bias in the gross power.

In Dudgeon, differences between *ctrl* and *wakes* (or adding wind farms at microscale - *ctrlWF*) input are not large indicating that mesoscale wake effects are not that significant.

The impact of the modeler can also be observed in the results, with two participants using WindPro (participants 5 and 8) and each one using different approaches to parameterize the wake models resulting in an overall spread in the metrics of around 2%.

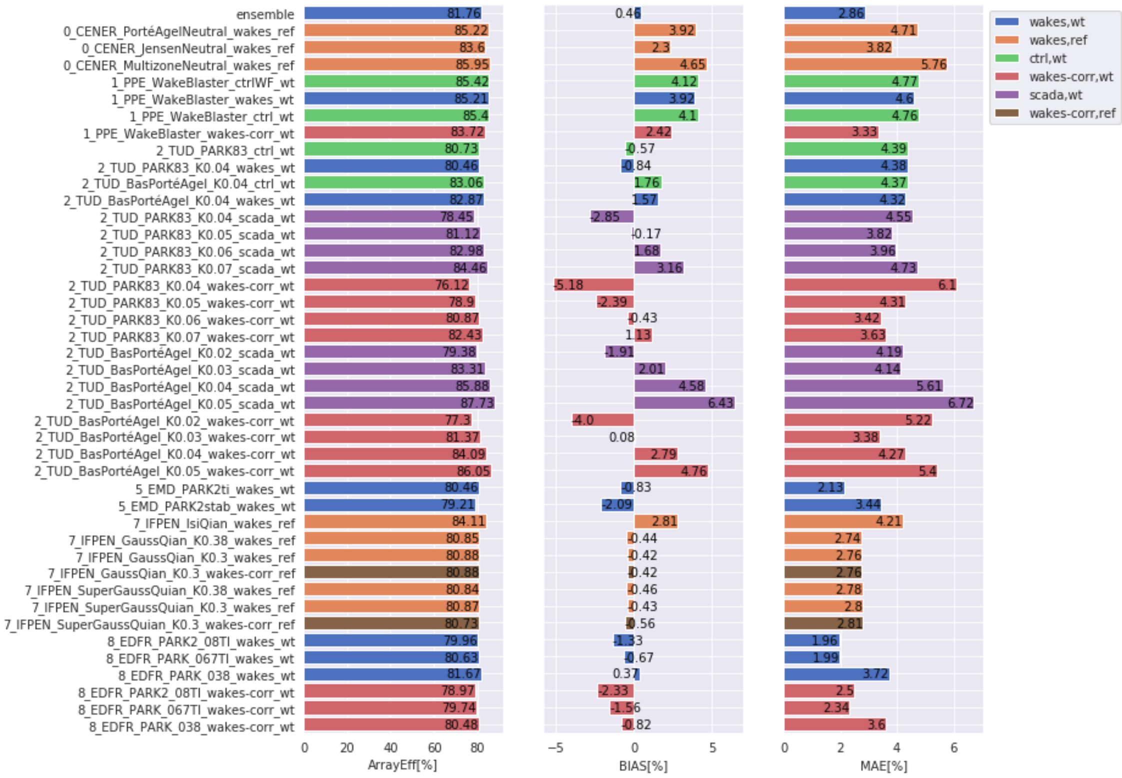

Figure 4: Overall metrics for Dudgeon wind farm. Simulations categorized by input data.

While wake models can predict the overall wind farm array efficiency with less than 1% bias in some situations, it is through error compensation between turbines inside the array and between bins. Array efficiency at turbine level is difficult to predict accurately and errors as large as 30% are often found, especially in stable and neutral conditions (Figure 5). This limits the capability of using engineering wake models in wind farm design optimization.

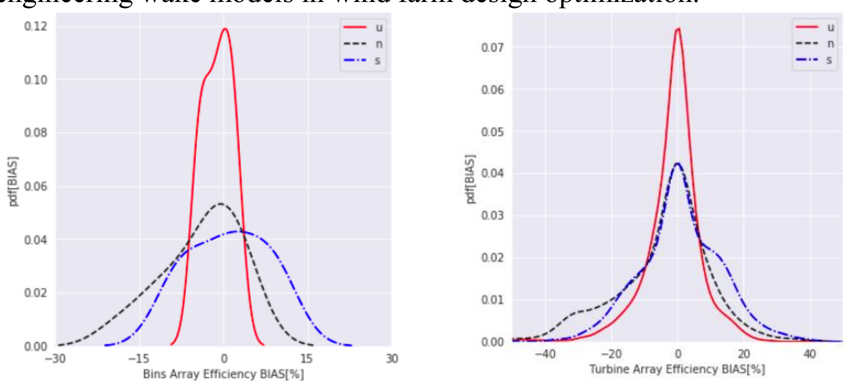

Figure 5: Distribution of BIAS for the ensemble model at bins and turbine levels for Dudgeon.

Conclusions

As larger and more closely spaced offshore wind farms are deployed the focus in array efficiency prediction is shifting towards producing more realistic inflow conditions that include large-scale phenomena like wind resource gradients that can result in variations of the gross power of more than 20% across the wind farm. Meso-wake modeling approaches can incorporate heterogeneous inflow in array efficiency prediction but the assessment is still limited by the lack of suitable validation datasets.

The OWA Challenge shows the benefits of implementing a systematic assessment of wake models based on operational data from industry. Still, it is difficult to assess array efficiency prediction when the background wind resource is not measured at the site and has to be inferred from SCADA data that are affected by stream-wise gradients and turbine performance and interaction effects. While engineering wake models can predict array efficiency with less than 1% bias, this is through compensation of errors inside the wind farm and between wind climate bins. Errors at individual turbines between 10 and 50% are frequent limiting the performance of layout optimization tools and the application of wake management control strategies.

An open-source model evaluation methodology allows mitigating uncertainties in energy yield assessment by reducing the scatter between models through collaborative benchmarking, by enabling traceable results and by identifying knowledge gaps that should be prioritized in future model developments, experiments and validation activities. To this end, the methodology is integrated in the IEA-Wind Task 31 "Wakebench" validation framework for further uptake [36].

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