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Exploring cooperation between wind farms: a wake steering optimization study of the Belgian offshore wind farm cluster

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Exploring cooperation between wind farms: a wake steering optimization study of the Belgian offshore wind farm cluster

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Abstract. In recent years, significant research efforts have focused on increasing power extraction using wake steering through yaw misalignment. In the current work, we evaluate the potential increase in annual energy production (AEP) for the Belgian offshore wind farm cluster using the FLORIS framework. The 2.2 GW Belgian cluster is an excellent test case to explore cooperation between wind farms as the concession zone is split into nine individual farms, resulting in a mix of intra- and inter-farm wakes to be considered in one of the largest wind farm clusters operational to date. Furthermore, the cluster high power density with relatively low turbine spacings is found to be responsive to wake mitigation strategies. Three different cost functions are compared. The first one is the complete cluster yaw angles optimization. The other two are farm-based optimizations seeking to maximize either their own AEP or the cluster AEP. Results show that all wind farms benefit from every optimization, encouraging operators to implement this strategy. The cluster optimization is found to be the one providing the best AEP increase for all wind farms individually and thus for the cluster. The farm-based function optimizing the cluster AEP is in second place, encouraging wind farm operators to collaborate for their own profits.

1. Introduction

In modern wind farms, wake interactions between neighbouring turbines are the main drivers of annual energy production (AEP) losses with typical loss values of 10% to 20% compared to lone-standing turbines [1]. The prospect of mitigating these wake losses through coordinated wind farm flow control has incited significant research efforts over the last two decades. Furthermore, a recent expert elicitation among stakeholders in academia and industry has shown that 84% of respondents believe that wind farm control will be broadly adopted in operational wind farms at some point in the future [2].

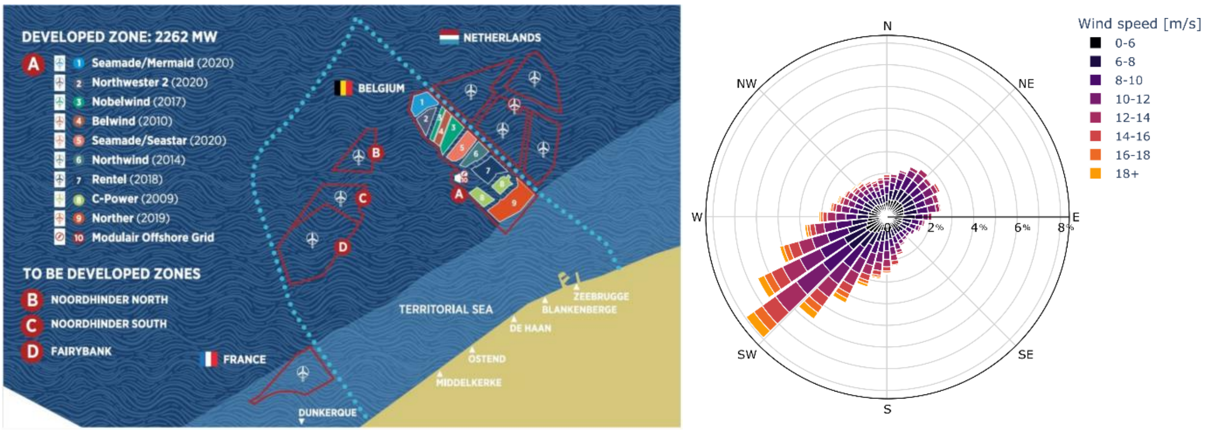
Over the years, several promising control strategies have emerged to either increase wake mixing through (dynamic) induction control [3,4] or steer wakes away from downstream turbines through intentional yaw misalignments upstream [5]. Comprehensive recent overviews of control techniques and architectures can be found, e.g., in [6] and [7]. In contrast to the complex fluid dynamics of (dynamic) induction control strategies, wake steering flow physics can nowadays be captured relatively well with fast analytical wake models due to significant research efforts in parameterizing phenomena such as wake curling and secondary steering (see, e.g., [8]), avoiding the need for complex flow models in designing control strategies. Combined with an increasing number of wind tunnel validation studies of simplified setups [9] and field campaigns in small sets of neighbouring turbines [10, 11], this has resulted in a significant increase in maturity of wake steering strategies in recent years, with first implementations becoming commercially available [12]. Despite this, studies on the potential AEP increase that wake steering could bring to modern operational wind farms at full scale in actual meteorological conditions have been relatively scarce.

Furthermore, with increasing deployments of offshore wind farms, e.g., in the North Sea, multi-gigawatt scale wind farm clusters, in which farms owned by different stakeholders operate in close proximity, will become more prevalent in the near future. A present-day example hereof is the offshore Belgian-Dutch offshore wind farm cluster located in the North Sea at the border between Belgium and the Netherlands, which consists of a total capacity of 3.7 GW distributed across 7 groups of stakeholders. Although from a fluid dynamics perspective these clusters can often be regarded as a single large wind farm (potentially with different types of turbines), the distributed ownership of individual farms can create distinct borders in operational strategies throughout the cluster. In view of wind farm control, the absence of full cooperation across different operators would likely result in greedy control optimization for individual operators yet sub-optimal conditions from a systems perspective. To the authors' knowledge, the potential impact of full cooperation on AEP at the farm as well as the cluster level has not been studied to date.

In this manuscript, we first describe the methodology used with a focus on three different wake steering cost functions, two of which include cooperation of all wind farms in a cluster, whereas the third optimizes controls for the benefit of each wind farm separately. Firstly, the wake modelling and optimization methodology is described in Section 2. Wake models of the FLORIS framework are compared to Large Eddy Simulations (LES) data of the Horns Rev wind farm from literature in Section 3. Next, Section 4 discusses the potential AEP increase from yaw optimization at cluster, farm, and turbine levels. Finally, conclusions are given in Section 5.

2. Methodology

In the current study, the focus is on the existing Belgian offshore wind farm zone, which was finished in 2020. The zone consists of 9 individual wind farms (Figure 1a), namely Mermaid, Northwester 2, Nobelwind, Belwind, Seamade, Northwind, Rentel, C-Power and Norther, run by 4 distinct operators. For the purpose of this study, we consider each wind farm being operated by a single operator. Furthermore, considering the wind rose (Figure 1b) is dominated by southwesterly winds, for simplicity we omit the Dutch Borssele wind farm zones on the northeastern border of the considered wind farms.



(a) (b)

Figure 1 : (a) Illustration of the Belgian offshore wind energy zone. Figure courtesy of the Belgian offshore platform[1]
(b) Wind rose of Belgian North Sea conditions at (51.5° N, 2.5° E) derived from the ERA5 dataset[13].

The wind rose used in this work (Figure 1b) was derived from the ERA5 dataset [13]. More specifically, it was generated from hourly data of the wind speed over 10 years (2012-2021) at

[1] belgianoffshoreplatform.be/en/news/wind-farms-in-belgian-north-sea-provided-green-power-for-nearly-2-million-belgian-households-in-2021/

coordinates 51.5°N, 2.5°E in the northwest of the Belgian North Sea and 100m altitude. This altitude lies in the hub heights range of studied turbines and FLORIS extrapolates wind speeds vertically using the wind shear exponential law. A shear exponent of 0.054 is used as computed in [14] with LiDAR measurements in the Dutch North Sea. As the maximum speed in the set is 27.7 m/s, 28 wind speed bins of 1 m/s are used. The choice of wind direction bin size can impact the results as it can hide specific wake-turbine interaction patterns [15], some of which may have high potential for optimisation. After a sensitivity study and mainly for computational cost limitations, the number of bins for the wind is set to 36 (10° resolution of the wind direction). This number is found to be conservative compared to more refined discretisation, meaning that it results in lower AEP increase after optimization of wind farm yaw angles.

Considering the relatively large amount of 399 turbines to be optimized over 1008 wind conditions (28 wind speeds × 36 wind directions), the recently developed Serial-Refine (SR) branch-and-bound algorithm [16] is better suited than classic gradient-based algorithms which scale as a power law with the number of turbines, each adding a new dimension to the problem, while the SR algorithm scales linearly. The optimization of the Belgian cluster is defined by the following function

$$\max\left(\sum_{t,s,d=1}^{T=399,S=28,D=36} P_{t,s,d}\left(\alpha_{t,s,d}\right) \times f_{s,d} \times 365 \times 24\right), \tag{1}$$

where α is the wind turbine misalignment with the incoming wind. Indexes t/T, s/S, d/D stand for turbine, wind speed and wind direction, respectively. $f_{s,d}$ is the frequency of wind speed s and wind direction d.

This cluster-wide cost function would result in optimal yaw angles maximizing the global AEP of the whole cluster and requires full cooperation and coordination of all 9 wind farm operators. In addition, a second "Farm-based" optimization is defined for each farm, in which yaw angles from the studied wind farm are optimized and all other wind turbines remain aligned with the incoming wind. The optimization can have two goals: maximizing the AEP of the studied farm, i.e.

$$\max\left(\sum_{t^*,s,d=1}^{T=T_{wf},S=28,D=36} P_{t^*,s,d}\left(\alpha_{t^*,s,d}\right) \times f_{s,d} \times 365 \times 24\right), \tag{2}$$

or maximizing the AEP of the cluster, i.e.,

$$\max\left(\sum_{t,s,d=1}^{T=399,S=28,D=36} P_{t,s,d}\left(\alpha_{t^*,s,d}; \alpha_{\bar{t},s,d} = 0\right) \times f_{s,d} \times 365 \times 24\right). \tag{3}$$

In these equations, t^*/T_{wf} are turbines from the studied wind farm (subset of t) and $\bar{t} = t - t^*$.

Finally, optimized yaw angles are used to compute the AEP of the complete cluster. Note that, for the farm-based approach, individual wake steering optimizations are run independently for each wind farm in which turbines of other farms are aligned with the mean wind direction. In practice, this would correspond to a situation in which operators create a lookup table of optimized yaw angles while assuming other operators are not engaging in wake steering. Subsequently, the yaw angles resulting from these individual farm optimizations are combined before computing the cluster AEP. An alternative approach could be to anticipate wake steering in neighbouring farms during the farm-based optimization procedure, but this approach is not included here for simplicity and left for future work.

3. Comparison of wake models with LES

In this section, we illustrate that the low-fidelity models are able to reasonably capture wake effects by comparing them to those obtained from a high-fidelity LES. For this comparison, we use the Horns Rev 1 wind farm, which consists of 80 Vestas V-80 2 MW turbines with a rotor diameter of 80 m and a hub height of 70 m, separated from each other by 7 diameter lengths in both alignment directions. It spans a rhomboidal area of around 20 km^2 with an angle of 7°. Its operation is simulated using Gauss Curl Hybrid (GCH) and Cumulative Curl (CC) wake models (and two other non-gaussian wake models). The results (Figure 2) are compared to reference results from an LES study [17] with a numerical framework validated by wind tunnel experiments and field data. All calculations were run using a mean velocity of 8 m/s and a turbulence intensity of 7.7% at hub height, which are in good agreement with observations at Horns Rev 1 [17].

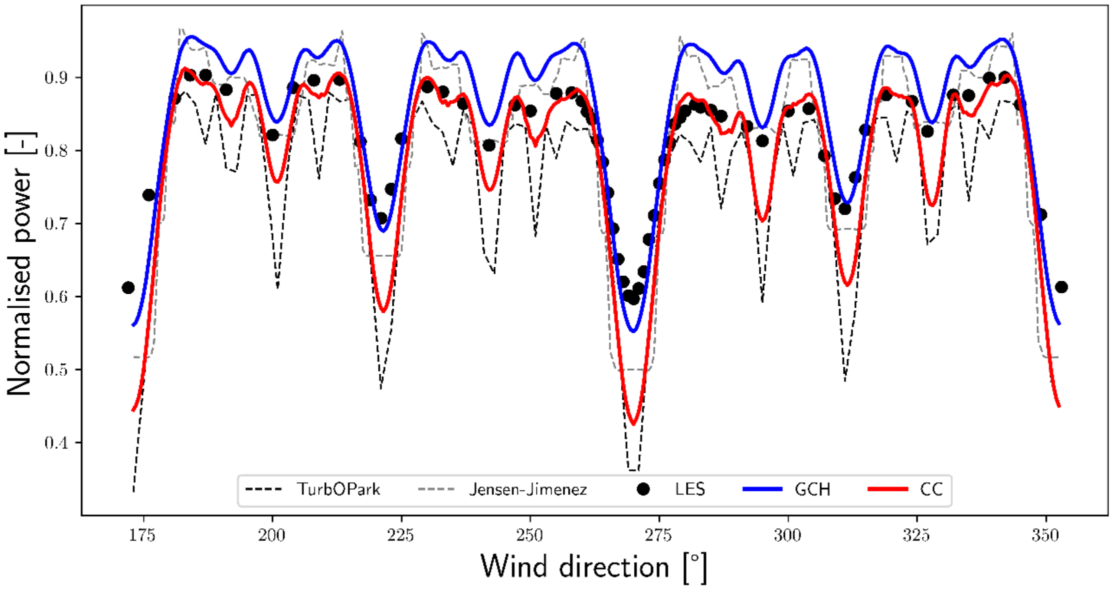


Figure 2 : Comparison of FLORIS wake models against reference LES results from [17] *for the Horns Rev wind farm.*

It can be seen that CC often exhibits too low dips but is otherwise quite close to LES, with a clear tendency to underestimate the power. On the contrary, GCH tends to overestimate the results although it reaches values very close to LES in the dips. This is consistent with conclusions from the original paper of the CC wake model [18]. Both curves have otherwise highly similar shapes.

Moreover, the CC wake model is designed specifically for large arrays of turbines where there are large wake losses. This is typically the case of the Belgian offshore cluster, where CC would show improved accuracy over the GCH model [18]. A thorough validation of the CC model for the Belgian cluster is left for future work. All wakes inside the cluster can physically be considered as typical "intra-farm wakes", even though they impact turbines of neighboring farms. As shown in [19] over the Rødsand and Nysted cluster, engineering wake models are suitable for turbine-to-turbine distances around 10 diameters. It is also noted that for large distances (over 30 diameters in [19]) the performance is decreased. Since the Belgium cluster is highly dense, inter-farm distances are comparable to intra-farm distances in [19]. The longest turbine-to-turbine distance in the cluster (in meters, between Norther and C-Power) is around 11.6 diameters. The longest inter-farm distance for Belwind (smallest turbine diameter) is around 10.9 diameters. Thus, the assumption of only intra-farm wakes is found to be reasonable.

As for the number of wind directions, the CC wake model is conservative compared to LES results and thus has been selected for the optimization study.

4. Results

In the following results, the impact of three cost functions (Cluster optimization, Farm-based optimizations maximizing either the studied farm or the cluster) on wind farm AEPs are compared using the increase in AEP. It is defined as

$$d\left(AEP_{t,s,d}\right) = \frac{AEP_{t,s,d}\left(\alpha_{t,s,d}\right) - AEP\left(\alpha_{t,s,d} = 0\right)}{AEP\left(\alpha_{t,s,d} = 0\right)} \; [\%] \tag{4}$$

where $AEP_{t,s,d}\left(\alpha_{t,s,d}\right)$ is the AEP computed after optimizing yaw angles and $AEP\left(\alpha_{t,s,d} = 0\right)$ is the AEP without yaw misalignment. On top of the wind rose, wind conditions are defined by a turbulence intensity of 6% and a wind shear coefficient of 0.054 which are common in the North Sea.

4.1. Comparison of cost functions

In this first part, results assess the effectiveness of the farm-based optimizations. In Figure 3, results show that all optimizations bring an important increase in AEP with a minimum of 2.14% for Nobelwind. However, wind farms are featuring some discrepancies, with outer wind farms (namely Mermaid and Norther) showing less difference, between the lowest farm-based optimization and cluster optimization, than inner wind farms. In fact, Mermaid and Norther show a difference of 0.17% and 0.25% respectively where Northwester 2 and Seastar differ by 1.25% and 1.20% respectively. This is due to the fact that the potential of maximizing the cluster AEP increases with large wake interactions between neighbouring wind farms. Outer wind farms have only one neighbour on one side (which on top of that is not in the dominant direction) where inner wind farms have two.

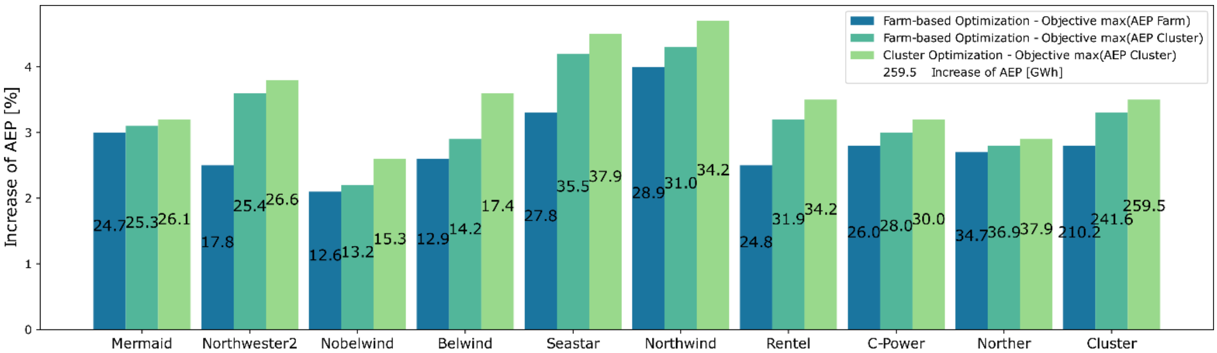


Figure 3 : Comparison of the AEP increases for the 9 Belgian wind farms.

Northwind, Seastar and Northwester 2 stand out from other wind farms with AEP increases of 4.22%, 4.15% and 3.58% for farm-based optimizations maximizing the cluster AEP. One reason for this is the high power density of these wind farms, which leads to high potential of controlling wind turbines through wake steering. As seen in Table 1, these three wind farms have the highest power density.

Mermaid	Northwester2	Nobelwind	Belwind	Seastar	Northwind	Rentel	C-Power	Norther	Cluster
14.43	19.01	12.41	14.58	16.18	17.81	13.18	14.89	10.46	14.04

Table 1 : Power density of Belgian wind farms and the Belgian cluster in MW/km²

With the idea of making the most electricity production out of the Belgian cluster, farm-based optimizations are compared to the complete cluster optimization which represents the highest achievable AEP using wake steering. The first thing to notice is that none of the wind farm maximizing their own AEP is able to achieve better production than the AEPs resulting from the cluster maximization. This means that all wind farm operators would have individual interests in collaborating with each other while at the same time maximizing the cluster AEP. As explained before, outer wind farms would have lower interest in collaborating than inner wind farms. The absolute AEP increases in GWh are showing the important amount of extra electricity produced by each wind farms and the cluster. The largely different installed capacities obviously lead to varying benefits.

Figure 4 is focusing on the Rentel and C-Power wind farms. The results of the two farm-based optimizations are showing their different objectives. The left figure is showing the farm-based optimization maximizing the farm AEP. Both Rentel and C-Power are having the same strategy of sacrificing AEP on the southwest turbines to increase everywhere else. This is clearly showing a lack of collaboration, especially for Rentel turbines that are in the wake of C-Power in the main wind directions.

The middle figure depicts the effect of collaboration between wind farms. Considering the wind rose, it is mainly C-Power losing AEP in the profit of Rentel, partially explaining that the difference between farm-based optimizations of C-Power is small whereas it is large for Rentel in Figure 3. With this collaboration, Rentel is now increasing the AEP of almost all its turbines where C-Power is losing much more AEP in the south part of the farm. However, C-Power overall AEP is improved since neighbouring wind farms are also collaborating. Finally, the right dot graph does not show a large difference with respect to results of farm-based optimization maximizing the cluster AEP (notice the lower range of AEP increase) as AEP seems to be increased uniformly over the farm, confirming that the cluster-based optimization is the best solution.

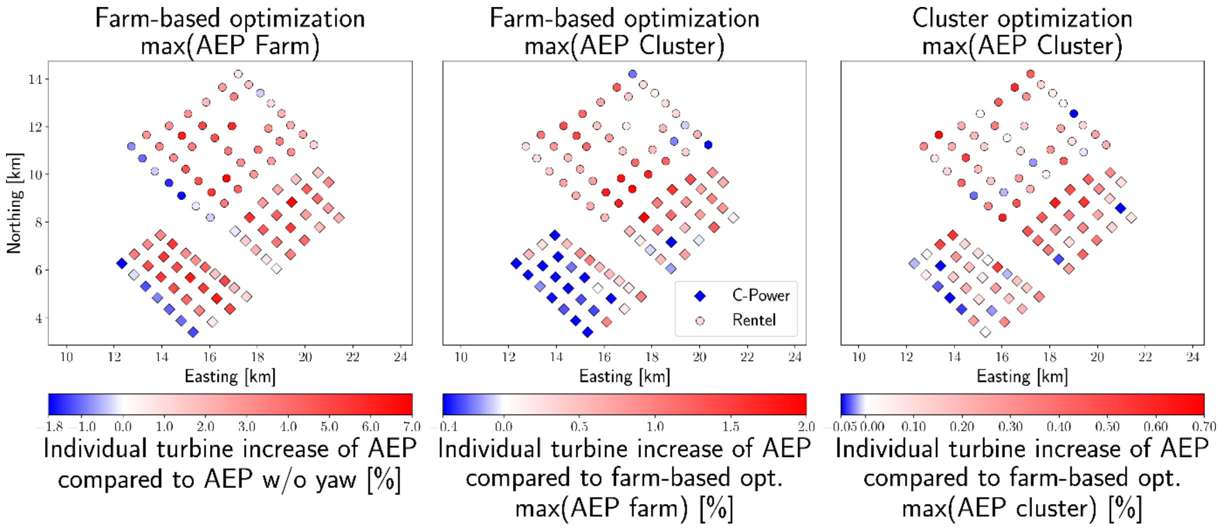


Figure 4 :Comparison of Rentel and C-Power individual turbine AEP increase for every cost functions.

To conclude, the cluster-based optimization is the one improving the most the electricity production of the Belgian cluster with 3.50% of AEP increase. This is highly non-negligible in terms of extra-profits generated by controlling wind turbines through wake steering. Without sharing data between wind farm operators, the farm-based optimization seeking to optimize the cluster AEP is out-performing the one optimizing individual AEPs (3.14% against 2.84%). These are still significant improvement of the AEP that should encourage wind farm operators to implement individually such control. In the following section, results focus on the cluster-based optimization providing more insights for individual turbine AEP increase and yaw angle.

4.2. Cluster-based optimization results

In an attempt to push the limits of AEP optimization through wake steering using FLORIS, all 399 wind turbines have been optimised as a single wind farm. Looking at Figure 5a, it is clear that the wake steering control is not uniform over the cluster since the absolute yaw misalignment occurrence varies. This metric is defined as

$$\alpha_t^{occ} = \sum_{s,d=1}^{S,D} |\alpha_{t,s,d}| \times f_{s,d} \tag{5}$$

where $f_{s,d}$ is the frequency of wind speed s and wind direction d. A clear trend indicates that southwesterly wind turbines are experiencing more yaw misalignment than downstream wind turbines along the dominant direction. This is well known in the field of control through wake steering and the goal is to deviate the wake of the front wind turbines (thus reducing power) to gain power at downstream turbines. It is validated with Figure 5b where these southwesterly wind turbines are the ones featuring a loss of AEP.

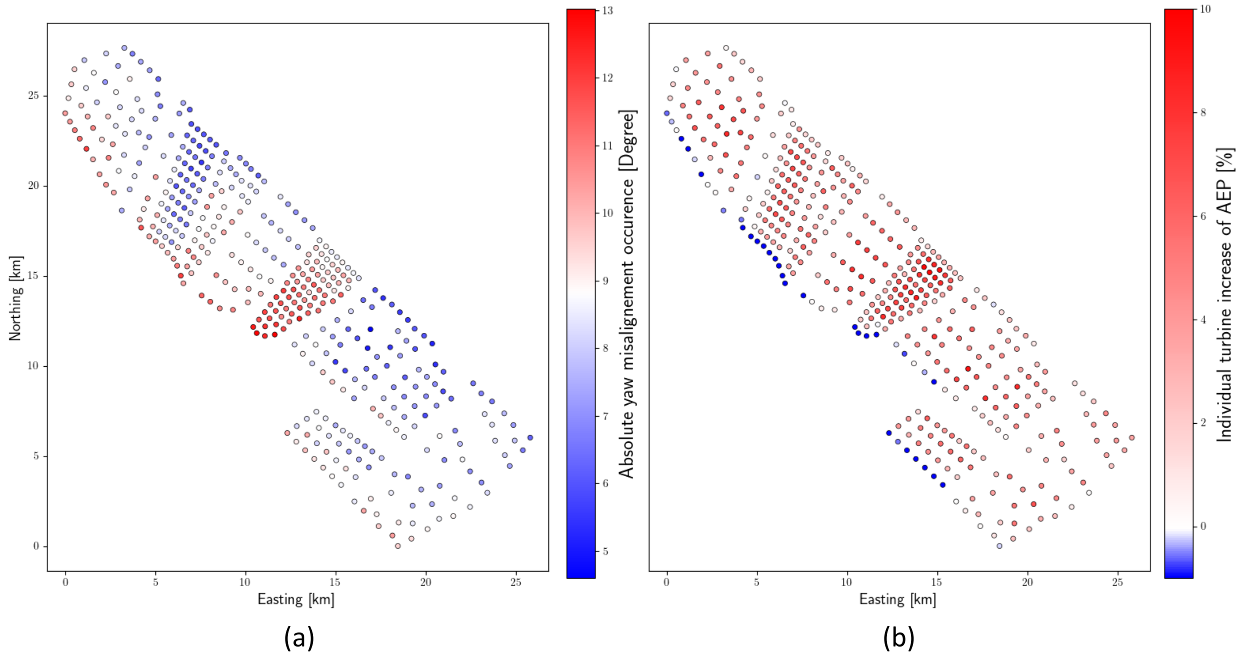


Figure 5 : Results of the cluster-based optimization showing (a) absolute yaw misalignment occurrence and (b) individual turbine increase in AEP.

As shown previously in Figure 3, the Northwind wind turbines have higher increase in AEP than turbines in the neighbouring farms. This is mainly due to the closely spaced layout of the farm which is well suited for control through wake steering. In fact, wake recovers with downstream distance, reducing the effectiveness of wake steering for largely spaced wind farm such as Norther. The drawback for Northwind is that its wind turbines are experiencing high yaw angle occurrences which are increasing loads and fatigue of the wind turbine blades and reducing their lifetime. However, this evaluation is out of the scope of this study.

Another closely spaced wind farm is Belwind, also featuring 3MW wind turbines but with a smaller diameter. Unlike Northwind, its yaw angle occurrences are low. One reason is that its rows of wind turbines have a significant angle with the dominant wind direction, making the wake naturally out of the downstream wind turbine rotor. This is confirmed in Figure 6 which compares Belwind and Northwind wakes without yaw misalignment for wind speed of 11.5 m/s, 230° wind direction, the wind conditions with highest probability at the cluster location (dominant wind conditions). With small yaw angle occurrence while showing a good AEP increase, Belwind might be the wind farm taking most advantage of this optimization.

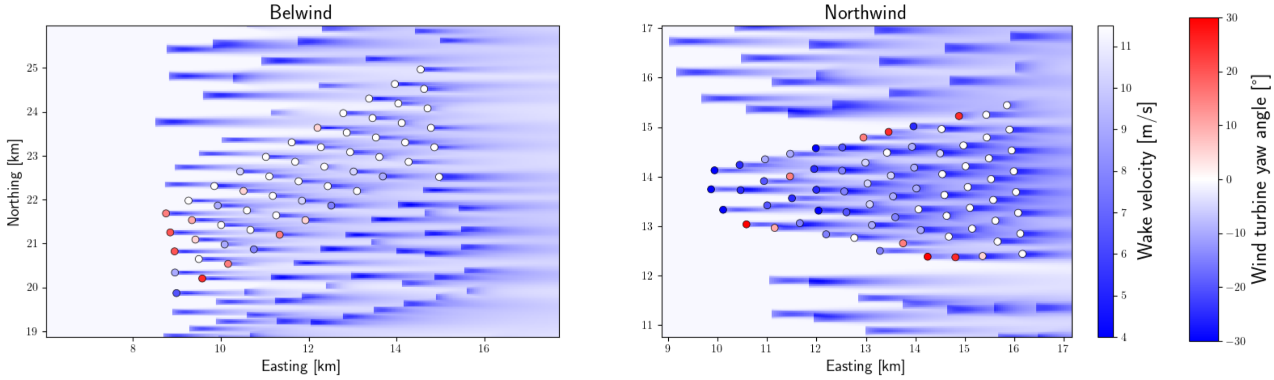


Figure 6 : Comparison of Belwind and Northwind wakes without yaw misalignment for wind speed of 11.5 m/s, 230° wind direction and 6% TI. Coloured dots are representing the optimized yaw angle solutions for these wind conditions.

Aside from the explanations given, some unknowns could be of important interest. For example, if a wind farm layout is already optimized for the site-specific wind rose, less AEP increase would be expected from the control optimization.

5. Conclusion

This paper explored cooperation between wind farms in order to increase the annual energy production of the Belgian offshore wind farm cluster through wake steering. The FLORIS framework is used with the Cumulative Curl wake model and the Serial-Refine yaw angle optimization algorithm. Three different cost functions are compared. The first one is the complete cluster yaw angles optimization. Other two are farm-based optimizations seeking to maximize either their own AEP or the cluster AEP. Results show that all wind farms benefits from every cost function, encouraging operators to implement wake steering control. The cluster optimization is found to be the one providing the best AEP increase for all wind farms individually and thus for the cluster. The farm-based function optimizing the cluster AEP comes just after, encouraging wind farm operators to collaborate for their own profits. As for future work, a thorough validation of engineering wake models with SCADA data will increase confidence in the results. Also, optimized solutions could be validated with mid- or high-fidelity models. Finally, this work could be incorporated into a multi-objective optimization including wind turbine loads or electricity prices.

Acknowledgements

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[13] was downloaded from the Copernicus Climate Change Service (C3S) Climate Data Store.
The results contain modified Copernicus Climate Change Service information 2020. Neither the European Commission nor ECMWF is responsible for any use that may be made of the Copernicus information or data it contains.

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