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# Wind farm set point optimization with surrogate models for load and power output targets

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**Abstract.** This study presents a methodology for wind farm set point optimization, which allows including both loads and power output as optimization criteria. The primary control strategy investigated involves de-rating of individual turbines in the wind farm. The optimal de-rating level of each individual turbine is determined by using accurate and computationally efficient surrogate models, mapping the dependency between the choice of de-rating strategy for a given turbine and the load and power outputs of downwind turbines. A case study based on the Lillgrund offshore wind farm shows that for specific wind directions with strong wake interactions, it may be possible to achieve a net gain in power output in the order of 5% at specific mean wind speeds. Alternatively, maintaining nominal power output but optimizing the load distribution could lead to substantial fatigue load reductions.

## 1. Introduction and study objectives

It is estimated that optimization of wind farm operations through improvement of the farm control strategies can potentially lead to 1-5% increase of the wind farm power outputs [1]. The modifications of the control strategy that are typically considered, aim at reducing the wake-induced losses by e.g. deflecting the wakes (wake steering) [2][1],[3], or de-rating (thrust reduction, also called induction control) [4] of selected turbines. In its most general form, such an optimization task would consist of modifying the control set points of individual turbines in the wind farm, and use the total profits (i.e., considering the balance of costs and income) as an objective function. Since estimating profits can be challenging, very often the total power output of the wind farm is used as an objective function instead of the profits. Such an approach still provides useful results since the power output is very closely related to the income from energy. However, changes in the control strategy do not affect only the power outputs, but also the mechanical loads of wind turbines. For example, de-rating the turbines by thrust reduction should also lead to reduction of loads on the de-rated turbine and reduction of wake effects downstream of the de-rated turbine [5]. It could therefore be beneficial to set up an optimization problem which balances the load levels with the power outputs, e.g., by making sure power is optimized without the loads exceeding the design limits, or by finding a set point which results in the desired power output with the smallest possible load levels. While the relationship between loads and costs is less explicit than the relationship between power output and income, loads can still be a useful criterion as the fatigue damage accumulation typically governs the actual turbine lifetime. In this respect, any fatigue damage increase could be considered as an increase in the turbine lifetime consumption and hence a reduction of the turbine lifetime. Further, if increased loading leads to the need of increased turbine maintenance, then load levels will affect operation & maintenance costs.



The main purpose of this study is to describe a methodology for wind turbine set point optimization through de-rating strategies, which allow loads and power output as the optimization criteria. The control strategy involves changing the rotor-speed and blade pitch set-points of individual turbines in the wind farm to reduce thrust and thereby wake effects. The optimal de-rating of each individual turbine is determined by using accurate and computationally efficient surrogate models, mapping the de-rating strategy for a given turbine with the load and power outputs of downwind turbines.

## 2. Methodology

We consider a wind farm with a number of turbines denoted by  $N_T$ . The optimization problem considers two types of output variables:

- Individual turbine output,  $P_i$ ,  $i = 1 \dots N_T$ .
- Damage-equivalent loads,  $DEL \propto (\Delta D)^{\frac{1}{m}}$ , where  $\Delta D$  denotes the fatigue damage accumulated at a single point in a wind turbine component over a reference period of 10 minutes, and  $m$  is the material S-N curve (Wöhler) exponent.

While the fatigue damage is the variable which governs the fatigue design limit state, it is often more convenient to work with damage-equivalent loads (DELs). DEL do not require other material characteristics than the S-N curve slope (Wöhler slope), while still being representative of the relative differences in fatigue damage caused by different loading conditions.

Using these power and load definitions, two potential optimization problem types are defined:

- 1) Power maximization:

$$\begin{aligned} & \text{Maximize } \sum_{i=1}^{N_T} P_i \\ & \text{Subject to: } DEL_i \leq DEL_{max}, \text{ for all } i = 1 \dots N_T \end{aligned}$$

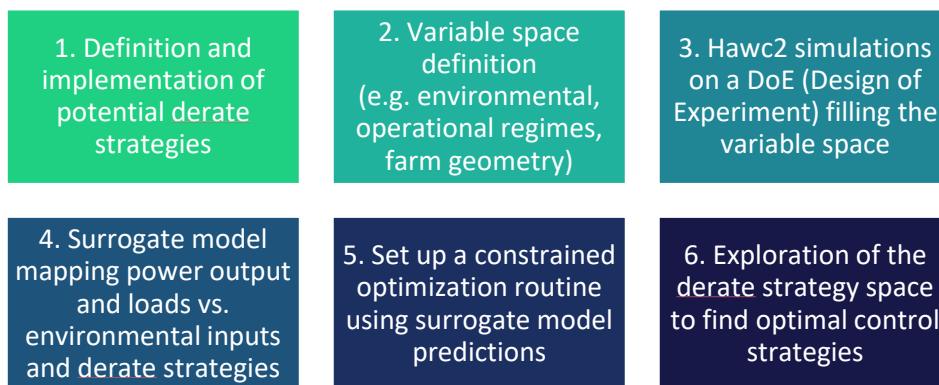
- 2) Fatigue minimization at target total farm power output  $P_{target}$ :

$$\begin{aligned} & \text{Minimize } \sum_{i=1}^{N_T} DEL_i \\ & \text{Subject to: } 1) \sum_{i=1}^{N_T} P_i = P_{target} \\ & \quad 2) DEL_i \leq DEL_{max}, \text{ for } i = 1 \dots N_T \end{aligned}$$

In the above,  $DEL_{max}$  is a fatigue damage equivalent load limit that could e.g. be based on the turbine design and ensure the current lifetime consumption rate does not exceed the design limits ensuring a minimum project lifetime.  $P_{target}$  is a target power output for the entire wind farm, and can be set by e.g. following the wind farm power curve, or it may be based on grid requirements such as power curtailment. The optimization variables are generator torque of the individual wind turbines and the minimum blade pitch angle. As the curtailed target power output is typically lower than the maximum potential power output at the present conditions, it is possible to use different combinations of control settings on individual turbines to obtain the same total target power. The goal of formulation 2) above would be to find the combination of control settings that leads exactly to the desired power output while accumulating the smallest possible amount of fatigue damage.

Solving the above optimization problem requires a model that can predict both power and loads on all turbines in the wind farm in a computationally efficient manner. Wake effects and upwind turbine de-rating need to be considered when computing the power and load predictions. The effect of these factors changes depending on the farm geometry, and corresponding to the turbine position inside the wind farm. Simulating the full wind farm behaviour for each optimization iteration is computationally

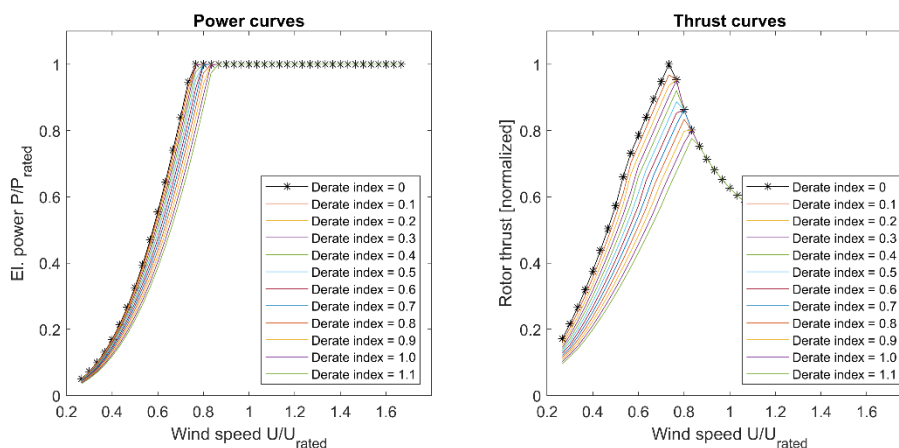
impractical. Therefore, we seek to map the behaviour of the aeroelastic model to a more efficient surrogate model that can be trained on a database with results from a pre-computed load simulations. Later, only the surrogate model is used during the optimization. In order to use gradient-based optimization methods, any surrogate model output needs to be at least first-order differentiable. This can be ensured by selecting the right surrogate model formulation, e.g. a polynomial-based model, or a neural network with suitable, continuous activation functions [6]. In the present study, we use the aeroelastic simulation tool Hawc2 [7] to generate a database of simulation results for the Lillgrund wind farm including both power and load estimates on major structures of the wind turbines under various inflow conditions and turbine control strategies. The simulation results are then used to train a neural network model which is then incorporated in an optimization routine. The suggested overall procedure for obtaining optimal de-rating strategies is outlined in Figure 1. In the remainder of this section, the details of the procedure are explained step-by-step.



**Figure 1** Steps in the implementation of the wind farm set point optimization routine

### 2.1. Implementation of de-rating strategy

De-rated operation of turbines is simulated by modifying the controller settings in Hawc2, leading to lowered mean rotor speed and increased blade pitch angle demand. Changes in the minimum blade pitch and the generator torque demand are applied, which results in reduced power along with reduced thrust; hence a reduction in the rotor induction and the strength of the wake deficit behind the turbine (Figure 2).



**Figure 2** Illustration of de-rating strategies. Left: power curve, right: torque curve

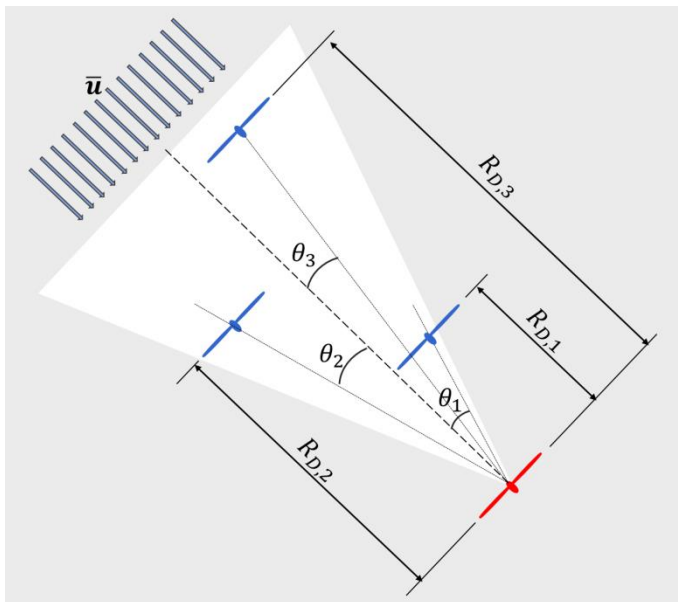
The amount of power de-rating applied to the turbines is quantified in terms of a derate index ( $DI$ ) which varies from 0 to 1 and controls the minimum blade pitch and the generator torque demand through the following relationships:

- Minimum blade pitch setting (in degrees):  $\varphi_{min} = -1 + 5DI$
- Torque demand multiplier setting:  $K = 0.7 + 4DI$

For a given high speed shaft rotational speed  $\omega$ , the constant  $K$  sets the generator torque demand  $T_g$  is given through the relationship  $T_g = K\omega^2$ .

## 2.2. Variable space definition

In addition to the derate index, the problem requires that environmental conditions and the effect of wake deficits are taken into account. We use the environmental variable space defined in [6] which consists of the wind speed  $u$ , turbulence  $\sigma_u$ , and wind shear exponent  $\alpha$ , and where the variables are considered independent and uniformly distributed within the pre-defined bounds of variation. This choice of variable distribution allows for uniform sampling of the design space, and is independent of the choice of site-specific distributions that may be used to sample from when e.g. computing annual energy production.



**Figure 3** Illustration of the parameterization used to define wake-induced effects

The effect of wakes on downwind turbines depends on the relative position between the turbines, the prevailing free stream conditions and on the operating regime of the upwind turbine. In order to establish a generalized model that can be applied on arbitrary wind farm layouts and turbine positions in the wind farm, the relative position and the operating regime of upwind turbines needs to be parameterized. We introduce the following approach:

- 1) For a given wind turbine and wind direction, a set of disturbing turbines is identified as those located within a sector of  $\pm\theta_{tol}$  degrees from the upwind direction (typically  $\theta_{tol}$  can be in the order of 20deg).
- 2) Each turbine in the disturbing set is characterized by three variables (Figure 3):
  - $R_{D,i}$ , the distance to the downwind turbine in rotor diameters;
  - $\theta_i$ , the relative angle between the upwind turbine direction and the wind direction, and
  - $X_{op,i}$ , the operating status of the upwind turbine. For the present study, the operating status is defined by the derate index, so  $X_{op,i} = DI_i$ .
- 3) In order to limit the potential number of variables, only the closest  $N_{upwind}$  turbines may be considered.

With the above approach, the number of variables required to model the power output and loads on a given turbine may vary based on the number of disturbing turbines and may be less than  $N_{upwind}$  or even be equal to zero. Depending on the choice of surrogate model type, this can be solved by either training a separate model for each case from zero to  $N_{upwind}$  number of disturbing turbines, or by assuming a fixed number of variables corresponding to the maximum number of upwind turbines  $N_{upwind}$ , and setting the unused variables to zero on a case-by-case basis. The latter approach is more convenient but is only applicable to surrogate model types that are able to learn sudden changes in variable behaviour - such as neural networks.

Based on these definitions, the total number of variables that will serve as inputs to a load and power surrogate model equals 3 (accounting for the environmental variables  $u, \sigma_u, \alpha$ ) + 1 (the derate index of the currently simulated turbine) +  $3N_{upwind}$ . Hence, if we choose  $N_{upwind} = 5$ , there will be a total of 19 variable inputs. Note that the free wind direction is not part of the variable space, but its effect is encoded in the variables because the set of disturbing turbines and the relative angles are determined by the free wind direction.

### 2.3. Load simulations for turbines in wake conditions using Hawc2 and the DWM model

Considering the present objectives, using empirical wake models is not sufficient as these models only describe the wake deficits and do not consider wind turbulence spatial-temporal time series or mechanical load time series as an output. We generate time-domain simulations of wind turbine response and power output using the Hawc2 aeroelastic tool [7]. Wake-induced effects are included in the simulations with the Dynamic Wake Meandering (DWM) model [8]. We look at quasi-static (open-loop) strategies on a 10-minute scale, hence the load simulations are with 10-minute duration. The outputs are the mean power output from each 10-minute period, as well as the DEL for several load channels: blade root flapwise and edgewise loads, tower base fore-aft and side-side, tower top fore-aft, side-side and torsion, and shaft torsion. Since all load channels would be used in a similar way, we only show results with blade root flapwise fatigue loads.

The distribution of the data sample for training the surrogate model should be chosen so that it covers the range of situations (e.g. site-specific climate, wind farm geometries) where the model is going to be used. If the intended use is for a specific wind farm or a few wind farms, an efficient sampling approach is to randomly pick scenarios representing these particular wind farms. Hawc2 simulations with the DWM model can include the wake effects of all wind turbines in a wind farm, however load time series are calculated on a single turbine only. Therefore, the sampling strategy is as follows: 1) environmental conditions (wind speed, turbulence and shear exponent) are sampled from their respective distributions, and a random  $DI$  level is selected for each turbine in the wind farm, 2) a random wind direction is picked from a uniform distribution between 0 and 360deg; 3) a random turbine position within the wind farm is selected; 4) a Hawc2 simulation for the selected turbine is carried out, under the wind direction, environmental conditions, and operating status of neighboring turbines as selected. The simulation results are then applied as the target data in the surrogate model training process, while the input variables are defined from the simulation inputs using the procedure described in Section 2.2. Based on the above, a large database of Hawc2 simulation results is generated, covering the relevant ranges of input conditions as well as varying combinations of de-rating strategies. The simulations in this database are used as inputs for training the surrogate model.

### 2.4. Surrogate model training

Wind farm setpoint optimization with gradient-based methods requires a computationally efficient and differentiable model for prediction of the loads and power output as function of external conditions and de-rating settings. Hence, the response of the aeroelastic model is mapped to a surrogate model based on feed-forward artificial neural networks. The architecture chosen includes 3 hidden layers with 100 units each, and the activation functions are hyperbolic tangents which ensure continuous and differentiable output of the regression model. The training is carried out using a back-propagation procedure with the Adam solver [9].

### 2.5. Alternative power predictions

Quasi-steady engineering wake models (such as implemented in PyWake [10],[11], FLORIS[12]) have an advantage over the time domain wake models in aeroelastic tools, due to their computational speed, and lack of statistical (realization-to-realization) uncertainty. At the same time, there are disadvantages since most engineering wake models do not take variables such as e.g. wind shear into account, and the wake meandering (motion of the wake deficit position with time) is only considered in a statistical sense. The realization-to-realization uncertainty due to using the DWM and turbulent incoming wind can be reduced by running multiple simulations under the same average conditions, but with different turbulence realizations as inputs. Since running the DWM with so many simulations may be computationally prohibitive, an alternative is to use a quasi-static engineering wake model for the power predictions. In the present study, both approaches were used: one surrogate model for power prediction was trained on Hawc2 simulation results and another model on PyWake predictions using the Bastankhah Gaussian wake model [13]. A comparison indicated similar power predictions at low turbulence, however the model based on Hawc2 results shows more scatter in power for cases with three or more turbines in a row. This is a consequence of the realization-to-realization uncertainty inherent to the time-domain simulations with turbulent wind, and means that more data would be required for a Hawc2-based power prediction model to achieve similar uncertainty level as the models based on static wake formulations. For the load prediction model however, the aeroelastic load simulations have no clear alternative. In the following section, results from several simple cases and optimization scenarios are shown. They are based on surrogate models for power prediction based on PyWake calculations, and surrogate models for load prediction based on Hawc2 simulation results.

### 3. Results with example optimizations

We use the Lillgrund offshore wind farm (Figure 4) to virtually implement the setpoint optimization procedure, including example scenarios. The purpose of these examples is to demonstrate specific details of the application of the optimization procedure as outlined in Figure 1, and not to recommend particular control strategies. The Lillgrund wind farm is considered relevant as an example due to its dense layout which results in significant wake losses. In the majority of comparisons we show results for wind directions of 220deg (south-west) or 300deg(north-west), for which up to 8 turbines are aligned in a row along the wind direction. This is considered as the scenario where the maximum potential benefit of the control strategy optimization can be shown. All examples considered are with ambient turbulence intensity of 10% and wind shear exponent of 0.1.

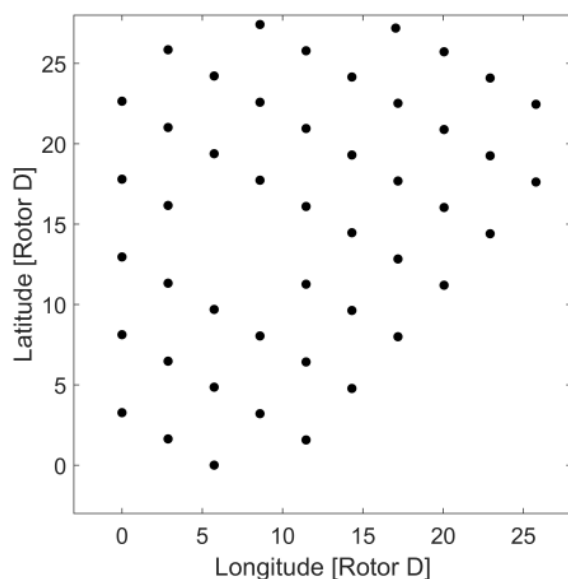
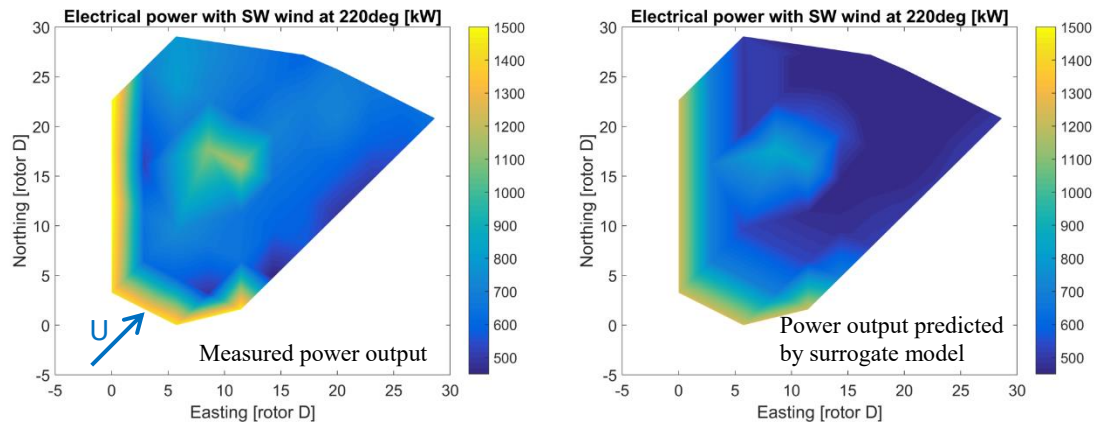


Figure 4 Lillgrund wind farm layout.



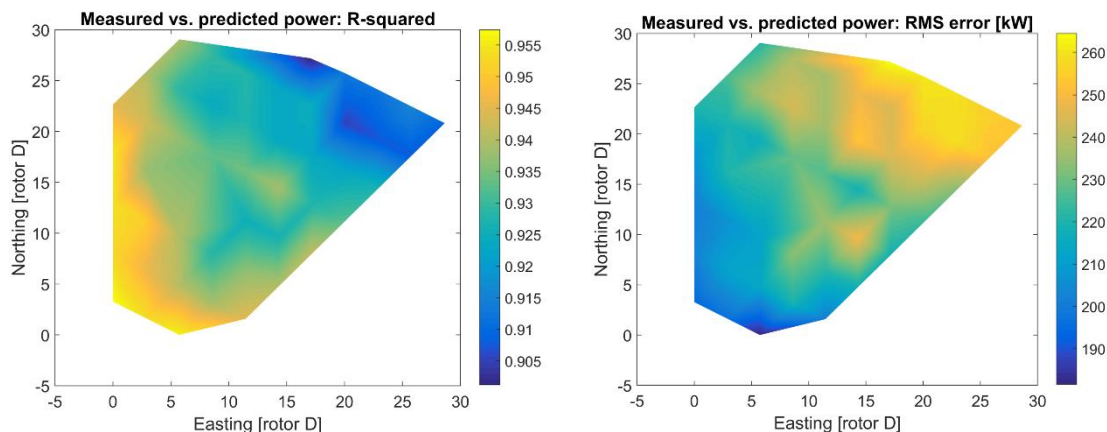
### 3.1. Surrogate model validation with SCADA data from normal operation without de-rating

SCADA data containing wind speed and power output time series from Lillgrund are used to validate the performance of the surrogate model in predicting the power output of individual turbines. As an example, a power output maps comparison for the specific case of 220 degrees wind direction and 9m/s free wind speed is shown in Figure 5. The surrogate model captures the pattern of power variation in the wind farm with reasonable accuracy.



**Figure 5** Comparison of measured power output and predictions based on a surrogate model. Wind direction is 220 deg and average free wind speed is 9 m/s.

The overall model performance is quantified by predicting the 10-minute mean power output of all wind turbines over a two-year measurement period. The free wind speed and wind direction are computed from the SCADA data of turbines in free wind conditions based on the approach described in [14]. The predicted power output of each individual turbine is compared against the actual 10-minute mean power output recorded in the SCADA. In order to avoid uncertainty regarding the influence of upwind turbines, only 10-minute periods where all 48 turbines in the wind farm are operational and producing power, are considered. The coefficient of determination ( $r$ -squared) of the model predictions varies between 0.9 and 0.96, and it is highest at the southwest edge of the wind farm, decreasing towards the north-east (Figure 6, left). This tendency aligns with the prevailing wind direction and indicates that the model uncertainty increases for situations where there is a large number of disturbing turbines. A similar pattern is visible with the RMS (Root Mean Square) error shown in Figure 6, right. The uncertainty shown in Figure 6 is not caused only by the surrogate model. Other contributors are the uncertainty in the estimation of the actual wind conditions from SCADA, and the model uncertainty (the power curve and wake effect modeling accuracy of Hawc2).

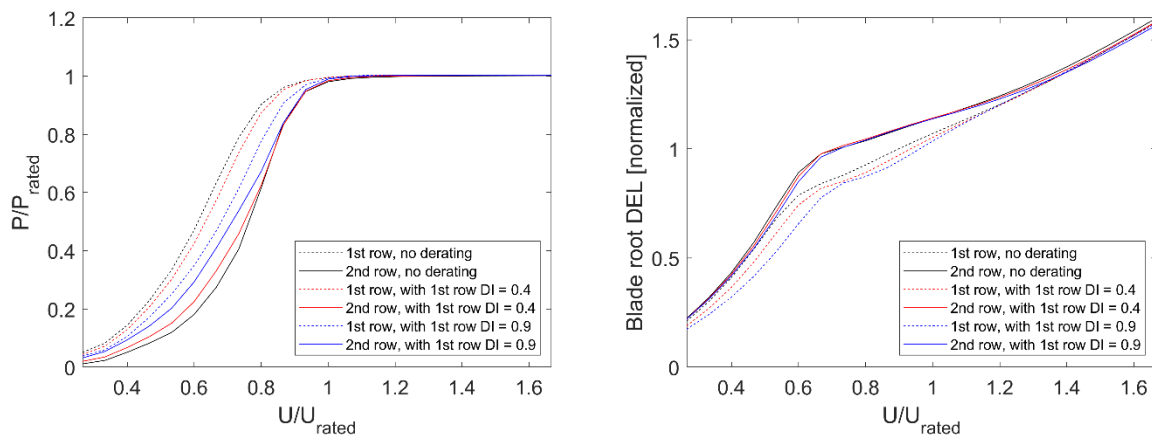


**Figure 6** Surrogate model performance in predicting individual turbine power output in the Lillgrund wind farm. Left: coefficient of determination. Right: Root mean square (RMS) error.

The following subsections quantify the powerful benefit of utilizing an accurate surrogate models towards planning optimal wind farm operation.

### 3.2. Load and power output visualisation under a selected de-rating scenario

In order to illustrate the effect of de-rating on load and power variation, an example of a pair of turbines is first considered. The two turbines are 5 rotor diameters apart, and the incoming wind is fully aligned with the line connecting the two turbines, so that the second turbine (row 2) is fully in the wake of the first turbine (row 1). The power curves and the blade root DEL for both turbines are evaluated as function of wind speed, and for three different values of the  $DI$  for the turbine in row 1 (the upwind turbine). The results, shown in Figure 7, demonstrate how de-rating the upwind turbine leads to decreased power output for the upwind turbine, but also to an increase in power output of the downwind turbine.

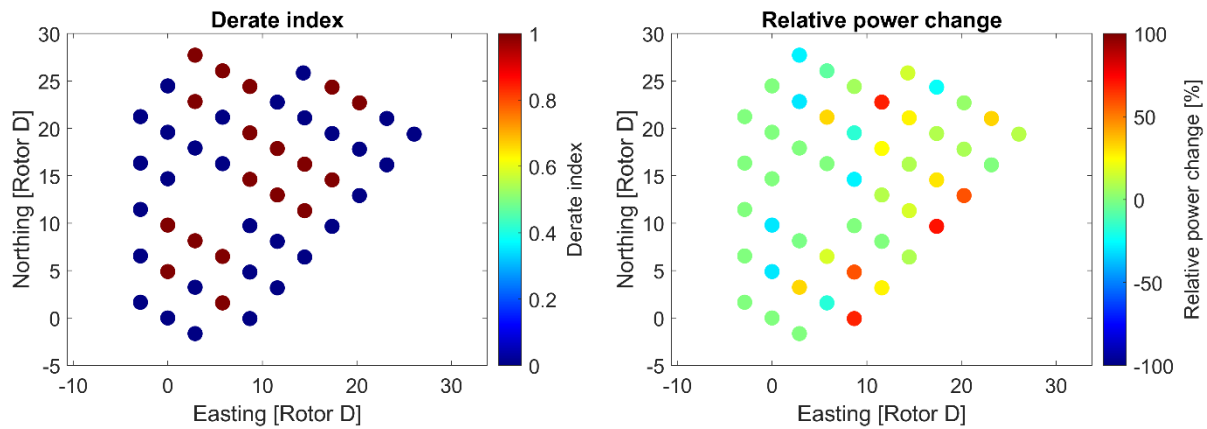


**Figure 7** Left plot: Power curves for a pair of turbines, where T01 (1st row) is in free wind, and T02 (2nd row) is downwind of T01. Changing de-rating levels in the first row affects the power curve of the second turbine. Right plot: Blade root flapwise DEL under the same conditions.

For the blade root flapwise DEL, the most visible effect of derating is on the upwind turbine (Figure 7, right plot), however there is also a small change in loads on the downwind turbine. The relatively small effect on the downwind turbine indicates that the blade loads are governed not only by the mean (or rotor-equivalent) wind speed, but also by the wake-added turbulence.

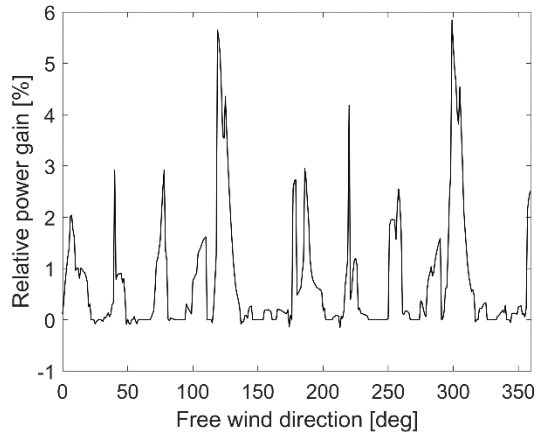
### 3.3. Example optimizations

We first consider maximization of the power output under strong wake conditions with imposed load constraints for a single wind speed of 9m/s and wind direction of 300deg, which is along the turbine rows with the tightest spacing in the wind farm – 3.3 rotor diameters. The load constraint level equals the maximum of the load estimates from all turbines in the wind farm for the nominal case (without derating) under the same environmental conditions. The resulting optimal de-rate levels are shown in Figure 8 (left plot), while the expected relative change in power output is shown on the right plot in the same figure. The optimal results provide 5.8% relative power gain, and it suggests that some turbines mostly in the center of the wind farm should be de-rated with  $DI \approx 1$ . The suggested strategy would also result in a net decrease in blade root flapwise DEL of approx. 14%, computed as the sum of the DEL over the entire wind farm. For individual turbines, the change in loads varies from 47% reduction (for strongly de-rated turbines) to 23% increase for turbines in the wake of a de-rated turbine. Despite the load increase on some turbines, no load constraints are active since the affected turbines are in the far-downwind part of the wind farm, where the effective wind speed and subsequently the fatigue load accumulation are relatively low.



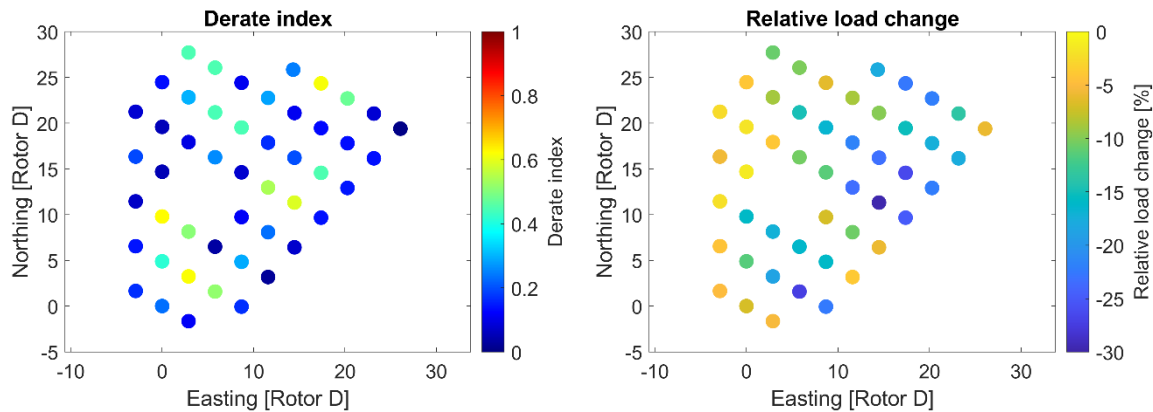
**Figure 8** Example suggested de-rate strategy for wind speed 9m/s and wind direction of 300 deg, resulting in 5.8% relative power gain. Left: derate indexes, right: change in relative power output of individual turbines.

Maximization of the power output without constraints is now performed for a free stream wind speed of 9m/s, but with wind direction sweeps from 0 to 360deg in one degree steps. The resulting relative power gains are shown in Figure 9. The predicted power benefit varies from zero at wind directions less affected by wakes, to almost 6% at 120deg and 300deg directions which are aligned with the rows with tightest spacing. The prominent peaks in Fig. Figure 9 are all at wind directions exactly along tightly spaced rows of turbines (3.3D, 4.3D, 4.9D).



**Figure 9** Maximum relative power gain from de-rate based strategy optimization, as function of wind direction, at 9m/s mean free wind speed.

Finally, we perform minimization of the total accumulated fatigue damage equivalent load over the wind farm, subject to minimum power constraints. We use the same case as in the first example, with 9m/s free wind speed and 300deg wind direction. The nominal wind farm power output (the expected output without any de-rating strategy) is targeted as an equality constraint, and the sum of the expected 10-minute blade root flapwise DEL over the entire wind farm is subjected to minimization. The resulting recommended strategy is with  $DI$  between 0 and 0.7 (Figure 10, left), and the outcome is approx. 18% reduction in the overall fatigue load accumulation, where for the individual turbines the relative reduction varies between 0 and 30% (Figure 10, right).



**Figure 10** Results from control strategy optimization aimed at load minimization. Left: derate index targets. Right: relative change in accumulated blade root flapwise DEL as a result of control strategy optimization. Wind conditions are 9m/s mean free wind speed and 300deg wind direction.

#### 4. Discussion

We showed relevant optimization examples for a dense offshore wind farm, which showcased the potential for using a surrogate model and which resulted in an increase of the total power output by several percent, or in substantial fatigue load reduction. However, this should not be considered as a recommendation for a specific control strategy, it is rather an illustration of the surrogate model approach for wind farm optimization.

The predicted changes in power outputs due to control strategy optimization were in the order of 0-6% in the scenarios considered. Model uncertainties are likely of similar order of magnitude. Therefore, it is important to reduce the uncertainty where possible, e.g. by using more and better-distributed data samples for surrogate model training, surrogate model hyperparameter tuning, and similar.

In some cases, the suggested de-rate strategies were close to binary (either  $DI \approx 0$  or  $DI \approx 1$ ). This indicates that there could be even broader range of thrust settings that could be explored. Note that  $DI \approx 1$  does not mean the turbine stops operating, instead it is running at a reduced-thrust setting but still producing about 75% of the nominal power (for wind speeds below rated).

The solutions obtained by an optimization run may be non-unique, there may be multiple local maxima due to geometry patterns and overfitting. The potential existence of such situations was verified by making multiple runs of the same optimization problem using random initialization of the optimization variables. For the problem presented in the first example, power maximization at 9m/s and 300deg wind direction, the random initializations resulted in similar expected power gains (between 5.3% and 6%). However, the locations of the turbines where de-rating should be applied changed slightly from case to case.

In the present study, we assumed that fatigue loads can be considered as a proxy for costs (e.g. due to design lifetime consumption, O&M costs). Any more advanced cost function based on a combination of loads & power output is also applicable to the same procedure. Moreover, combining the load predictions with structural limit states could allow using structural reliability [15],[16] as an optimization criterion in the same framework.

#### 5. Conclusions

We developed and demonstrated a surrogate model based optimization that allows individual turbine control set point variation for all turbines in a wind farm, under multiple optimization criteria including minimal damage-equivalent loads or maximum power. Key benefits of this approach include:

- The overall possibility to include loads as optimization criteria;

- The surrogate-based approach is very computationally efficient, once the simulation results have been generated
- It can work with multiple constraints and objective functions, allows considering both power output, loads and reliability
- Same principle can be directly applied with more advanced objective functions such as e.g. LCOE or reliability (as long as these are derived from power and loads)

It was seen that for specific wind directions with strong wake interactions, it may be possible to achieve a net gain in power output in the order of 5% at specific mean wind speeds. Alternatively, maintaining nominal power output but optimizing the load distribution could lead to substantial fatigue load reductions.

Some potential challenges with the approach were also identified. This includes the uncertainty in the surrogate model, narrowing it down may require many data samples. The final accuracy of predictions is always limited by the accuracy of the wake model used in the data generation phase. Therefore, further research in this area could potentially focus on the problem of uncertainty reduction in the wake modelling and surrogate modelling.

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