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Mitigating Turbine Mechanical Loads Using Engineering Model Predictive Wind Farm Controller

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Abstract.
Cumulative O&M costs of offshore wind farms can amount to 38% of lifetime costs. In wind farms, upstream turbine wakes can result in up to 80% higher fatigue loads at downstream wind turbines. The present work therefore investigates to reduce wind turbine fatigue loads during the provision of grid balancing services using model predictive wind farm control. The main objective of the developed controller is to follow a total wind farm power reference and to reduce the damage equivalent tower bending moments of the turbines in the wind farm. The novelty in the control approach is the use of an engineering model-based, linear wind farm operation model and a newly developed wind farm-scale wind turbine fatigue load model. The model predictive controller is compared with commonly used wind farm control approaches in two wind farm case studies using a dynamic wind farm simulation tool. The simulation results suggest that the proposed model predictive controller can reduce the sum of the equivalent tower bending moments of wind turbines in a wind farm during provision of ancillary services. Simulations of an eight turbine array show up to 28% lower sum equivalent tower moments as compared to commonly used wind farm controllers. The observed reduction in turbine fatigue loads is attributed to the use of adequate wind farm-scale wind turbine fatigue load models.

Nomenclature
0.1. Abbreviations

CFD	Computational fluid dynamics
D	Rotor diameter
O&M	Operation and maintenance
MPC	Model predictive control
PI	Proportional-integral

0.2. Indices

i	Index of downstream turbine
l	Index of upstream turbine

1. Introduction
Cumulative O&M costs of an offshore wind farm can amount to 38% of lifetime costs [1]. These wind farm O&M costs are to some degree a function of wind turbine fatigue loads. In wind

farms, upstream turbine wakes can result in up to 80% higher fatigue loads at downstream wind turbines [2]. Therefore the mitigation of wind turbine wake-induced fatigue loads is of importance.

Existing studies [3]–[6] have investigated the reduction of wind turbine fatigue loads during the provision of ancillary services using model predictive wind farm control. However, the investigated approaches use controller objective functions and wind farm operation models, that are not useful for achieving a reduction of turbine fatigue loading in a real wind farm. The proposed objective functions are typically a combination of squared turbine bending moments and the deviation of wind farm power from the reference. Fatigue damage, however, depends on the number of cycles, in addition to their amplitude, and damage accumulates with an exponent that is much higher than the square. It is therefore suggested to use measures of fatigue based on cycle counts, such as damage-equivalent bending moments, in the objective function.

Impediments to controller models are incomplete modelling and computational costs. For wind farm flow modelling, some approaches [3], [4] do not include a model for the aerodynamic interaction of wind turbines. As mentioned earlier, wake-induced fatigue loads are a major source of wind turbine fatigue loads. It is therefore beneficial to include the effects of wake interaction in the controller model. For this purpose 2D computational fluid dynamics (CFD) flow models [6], [7] are investigated, which estimate the hub height flow field in a wind farm. An impediment, however, to the use of such models for the control of large scale wind farms is computation time due to the amount of states used by these CFD models.

The present work investigates promising solutions to the above challenges. In the model predictive wind farm controller of the present work, aerodynamic wind turbine interaction is modelled using an engineering model-based wind farm flow model [8]. The model requires less than 5% of the states needed for a comparable 2D CFD flow model and thus is computationally faster. While computationally fast, the model has shown a wind speed prediction error of less than 5% with respect to reference tools. Further, the present work is - to the author's knowledge - the first to use a controller objective function that minimizes the sum damage equivalent tower bending moments of the turbines in a wind farm. The equivalent moments are modelled using a wind turbine fatigue load model, that is newly developed for this work.

In the next section, the methodology is detailed. Thereafter, the performance of the developed model predictive wind farm controller is compared to reference tools. The paper concludes with the key findings.

2. SimWindFarm simulation environment

The wind farm controllers are tested in the dynamic simulation framework SimWindFarm [9]. SimWindFarm performs simultaneous, dynamic simulations of the wind turbines in the wind farm, the wind farm control, the aerodynamic interaction of the wind turbines and the actions by the transmission system operator. The NREL5MW virtual turbine model [10] is used to model wind turbine operation. Wind turbine aerodynamics are modelled using the turbine power coefficient and thrust coefficient. Up to 3rd order dynamic models are employed to simulate the drive train, generator and pitch actuator. The aerodynamic model of the wind flow in the wind farm is structured into an ambient field model and a turbine wake model part. The ambient wind field is modelled as the hub height, turbulent wind flow advected with the mean wind speed under the assumption of Taylors frozen turbulence. Wake flow modelling includes wake wind speed deficit, wake width expansion, wake meandering and wake merging. The tested wind farm controllers are embedded in and tested through the DTU Wind Farm Controller framework [11], which is linked to the SimWindFarm simulation tool.

All simulations use the same wind conditions and a turbine spacing of 4.3D. The simulated wind conditions are a mean wind speed of 8m/s, a turbulence intensity of 6% and a constant wind direction along the turbine row.

3. Power reference following WFC

During the provision of ancillary services the operational objective of a wind farm is to follow an externally given total farm power reference signal. The present work investigates the use of a model-predictive controller (MPC), which is developed with the objective to reduce wind turbine fatigue loads. The performance of the MPC is compared to the commonly used, closed-loop proportional-integral (PI) wind farm controller.

3.1. PI - wind farm controller

Figure 1 shows the system structure of the closed-loop, PI-wind farm controller. The wind farm controller consists of a PI-controller and a power dispatch function. The transfer function $C(s)$ of the PI-controller is defined as

$$C(s) = k_p + \frac{1}{sT_i} \tag{1}$$

where k_p is the proportional gain and T_i is the time constant of the integrator. An Anti-Reset-Windup set-up is used to limit the integrator.
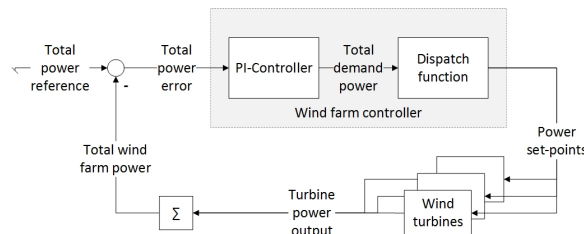

Figure 1. System structure of closed-loop PI-controller.

The PI-controller sets the demanded total wind farm power, which is distributed to the wind turbines in the wind farm using the dispatch function. The distribution of the demanded power $P^{WF}_{demanded}$ depends on the objectives of the wind farm operator. The present work investigates the use of a static distribution of turbine power set-points and a dynamic distribution of set-points according to available power. The static distribution of the turbine power set-points P^{WT}_i is set manually by the wind farm operator as

$$P^{WT}_i = f_i P^{WF}_{demanded} \tag{2}$$

where f_i is the fraction of the total demanded wind farm power dispatched to turbine i. f_i is consequently subject to

$$1 = \sum_{i=1}^{N} f_i \tag{3}$$

where N is the number of wind turbines in the wind farm.

In the dynamic distribution of set-points according to available turbine power the turbines set-points are defined as

$$P^{WT}_i = \frac{P^{WT}_{avail,i}}{P^{WF}_{avail}} P^{WF}_{demanded} \tag{4}$$

where P^{WT}_{avail} is the available power of turbine i and P^{WF}_{avail} is the wind farm available power. This approach was originally introduced in [12] and is termed proportional dispatch in the following.

3

3.2. Model-predictive controller

The objective of the model-predictive controller is to follow the total wind farm power reference while reducing the mechanical loads of the wind turbines in the wind farm. This control objective translates into the following MPC-cost function objectives.

- Follow total wind farm power reference
- Follow optimum turbine operation point derived from fatigue load model
- Reduce gust-driven mechanical loads

The control actions of the MPC are set to be constrained by the availability of aerodynamic power at the wind turbines in the wind farm. The MPC predicts the effect of the control actions on the performance of the wind farm using a linear, dynamic wind farm flow model and a statistical and deterministic mechanical load model.

Figure 2 shows the system structure of the wind farm operation model, which consists of a flow model, a turbine power model and a deterministic turbine mechanical load model.
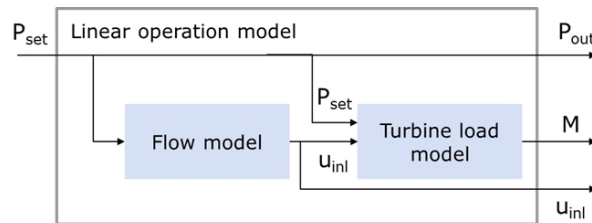

Figure 2. System structure of wind farm operation model.

3.2.1. Flow model The flow model consists of a set of modules, where each module accounts for the interaction of one or multiple upstream turbines and a single downstream turbine. These interaction models are joined together to a total flow model according to the overall aerodynamic interaction of the wind turbines in the wind farm.

The aerodynamic interaction of one or multiple upstream turbines with a downstream turbine is modelled as

$$u_i(t) = u_\infty(t - \delta t_\infty) - \sum_{l=1}^{L_i} \delta \tilde{u}_l(t - \delta t_l) \tag{5}$$

where u_i is the inlet wind speed of downstream turbine i at time t, u_∞ is the wind speed at the most upstream turbine and $\delta \tilde{u}_l$ is the wake deficit induced by upstream turbine l. L_i is the number of turbines upstream of turbine i. δt_∞ is the duration for the wake from the most upstream turbine to propagate to downstream turbine i. δt_l is the duration for the wake from upstream turbine l to propagate to downstream turbine i.

The wake deficit model is derived from that of Frandsen et al. [13]. The model is chosen as the same wake deficit model is used in the simulation environment, SimWindFarm. In general, the aim is to choose the wake deficit model used in the linear flow model as to match the target system as close as possible. In order to yield a linear model a linearized wake deficit equation is obtained from the 1st order Taylor-Series expansion of the Frandsen wake deficit model as

$$\delta \tilde{u}_l = \delta u_{l,0} + \frac{\partial \delta u_l}{\partial u_l}\Big|_{x_0} \Delta u_l + \frac{\partial \delta u_l}{\partial P_l}\Big|_{x_0} \Delta P_l \tag{6}$$

where Δu_l is the deviation of u_l from the wind speed linearisation point $u_{l,0}$ and ΔP_l denotes the deviation of P_l from the power linearisation point $P_{l,0}$. x_0 is the overall system linearisation point.

As a discrete time MPC approach is used the above equation (Eqn. 5) is converted to

$$u_i[n] = u_\infty[n - \kappa_\infty] - \sum_{l=1}^{L_i} \delta \tilde{u}_l[n - \kappa_l] \tag{7}$$

where n is the discrete time step with $t = n * T_s$ and T_s the sampling time. The discrete time delay κ is defined as $\kappa = (\delta t / T_s)_{round}$.

After converting Eqn. 7 to state space form and joining all wake interaction processes, the total wind farm flow model can be written as

$$\begin{bmatrix} \underline{u}_{del,all} \\ \underline{u}_0 \end{bmatrix}[n+1] = \begin{bmatrix} \underline{\underline{A}}_{del,all} + \underline{\underline{B}}_{u,all}\underline{\underline{C}}_u & \underline{\underline{B}}_{u_0,all} \\ 0 & I \end{bmatrix} \begin{bmatrix} \underline{u}_{del,all} \\ \underline{u}_0 \end{bmatrix}[n] + \begin{bmatrix} \underline{\underline{B}}_{\Delta P,all} \\ 0 \end{bmatrix} \Delta \underline{P}[n] \tag{8}$$

$$\underline{u}[n] = \begin{bmatrix} \underline{\underline{C}}_u & 0 \end{bmatrix} \begin{bmatrix} \underline{u}_{del,all} \\ \underline{u}_0 \end{bmatrix}[n] \tag{9}$$

$\underline{u}_{del,all}$ is the rotor effective wind speed delay states of all wind turbines, $\underline{u}_0$ is the wind speed linearisation point and $\underline{u}$ is the present rotor effective wind speed at the turbines in the wind farm. $\Delta \underline{P}$ is the deviation of the turbine power set-points from the power linearisation point. More details of the flow model can be found in [8].

3.2.2. Turbine operation model As shown in Figure 2 above, turbine power is modelled using a direct feed-through. As such the modelled turbine power output equals the turbine power set-point. This assumption is valid if the sampling time is much larger than the turbine generator dynamics.

In the present work, the considered turbine mechanical load is the tower front-aft bending moment. The tower bending moment M_{tower} is modelled as

$$M_{tower} = h * \frac{1}{2}u^2 \rho A c_T \tag{10}$$

where u is the rotor effective wind speed, h is the turbine hub height, ρ the air density, A the rotor swept area and c_T the turbine thrust coefficient. The tower bending moment model is linearized and used in the MPC to mitigate the effect of gusts on wind turbines.

3.2.3. Turbine fatigue load model The optimum turbine operation points used by the MPC are derived from a newly developed, statistical turbine fatigue load model. The model is a database of damage equivalent turbine tower bending moments in a range of relevant turbine operational conditions and wind conditions. The equivalent moments are obtained from simulations of a two turbine array using the SimWindFarm simulation tool. Figure 3 shows the layout of the two turbine array. The rainflow counting algorithm is used to derive damage equivalent moments from the simulated, dynamics of tower bending moments. In the rainflow counting algorithm a Wohler exponent of 4 is used, which is representative of steel. Figure 7 shows key results from the database of the turbine fatigue load model for the wind condition relevant for the simulation case.
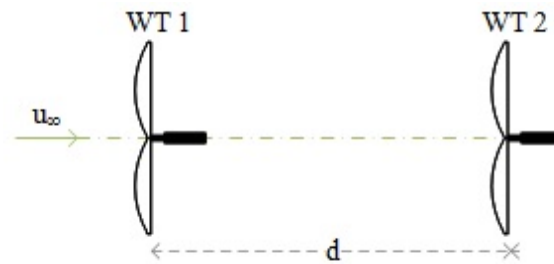
Figure 3. Layout of two turbine array aligned with wind direction.

4. Results & Discussion

The performance of the PI-controller and MPC are discussed in the following. First the models used in MPC are examined, and thereafter, the controllers are compared in two case studies. The first case study investigates a two turbine array and the second an eight turbine array.

4.1. Performance of linear wind farm model

The prediction accuracy of the linear wind farm model is examined using an eight turbine array simulated in SimWindFarm. Figure 4 shows the layout of the eight turbine array.
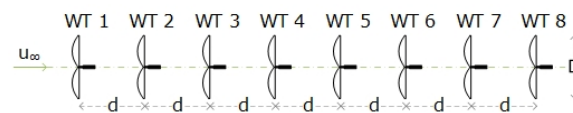
Figure 4. Layout of eight turbine array aligned with wind direction.

Figure 5 shows a comparison of the rotor effective wind speed between the linear wind farm model prediction and the true value from SimWindFarm at turbine No. 3. The linear model predictions agree well with SimWindFarm, showing a mean bias of 0.07m/s and root mean square error of 0.3m/s.
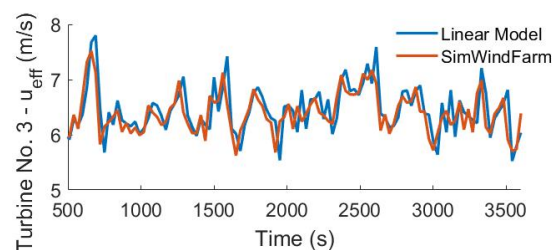

Figure 5. Comparison of rotor effective wind speed between SimWindFarm (true value) and linear wind farm model prediction at turbine No. 3.

The wind speed predictions are in even better agreement with SimWindFarm at the other wind turbines, as can be seen in Figure 6. The mean error bias ranges from an over-prediction of 0.003m/s to an over-prediction of 0.17m/s. The root mean square prediction error ranges from 0.08m/s to 0.3m/s at downstream turbines and is 0.5m/s at the upstream turbine. As such the maximum normalized root mean square error is 2% at the downstream turbines and 6% at the upstream turbine. The larger error at the upstream turbine is due to the wake model and the

definition of the wind speed state in the linear model. The interested reader is referred to [8] for more details on the model.
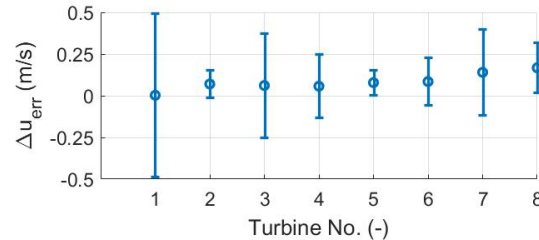

Figure 6. Rotor effective wind speed prediction error of linear, dynamic wind farm operation model for eight turbine array. Shown are mean (circle) and standard deviation (error bar) of prediction error.

4.2. Turbine fatigue load model

Figure 7 shows a contour plot of the sum of the simulated tower equivalent bending moments of a two turbine array, with a layout as shown in Figure 3. The equivalent moments are derived for turbine power set-points ranging between zero and the available power of the upstream turbine No. 1.
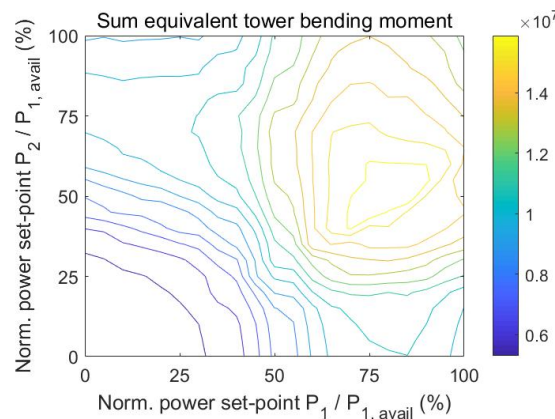

Figure 7. Contour plot of sum of simulated, equivalent tower bending moment of two turbine array.

As expected, an increase in a turbine's power output results in a larger tower bending moment of that turbine. For the sum of the two turbines' equivalent tower bending moment the total load minimizing power set-point distribution depends on the value of the total power reference. For a total power reference below 75% of the available power at turbine No. 1, the lowest sum equivalent moment is observed if the power set-point of both turbines is similar. Thus for a given reference total power, distributing the demanded reference total power to the turbines equally results in the lowest sum equivalent moment in this model. For a total power reference above 75% of the available power at turbine No. 1, the lowest sum equivalent moment is not achieved for an equal distribution of power set-points. Rather, the lowest sum equivalent moment is observed for the largest reduction of the upstream turbine power set-point possible, whilst operating the downstream turbine at maximum power and delivering the demanded total reference power.

4.3. Two turbine case study

The performance of the MPC is compared with the PI-controller in SimWindFarm simulations of the two turbine array with a layout as shown in Figure 3. The PI-controller uses the proportional

dispatch and static distribution dispatch functions. The choice of the static distribution shall mimic a wind farm operators desire to reduce wake loads on a downstream turbine. Thus, the static distribution is set to $\{f_1 = 0.2; f_2 = 0.8\}$.

Figure 8 shows the turbine power set by the wind farm controllers. During operation with the PI-wind farm controller with static dispatch, the turbine powers stay constant. With the proportional dispatch function, the largest variation in turbine powers is observed. The MPC operates the turbines close to the optimum power set-point derived using the statistical turbine fatigue load model. The variation of turbine power set-points by the MPC aims to mitigate gusts and ensures sufficient available power at all turbines.
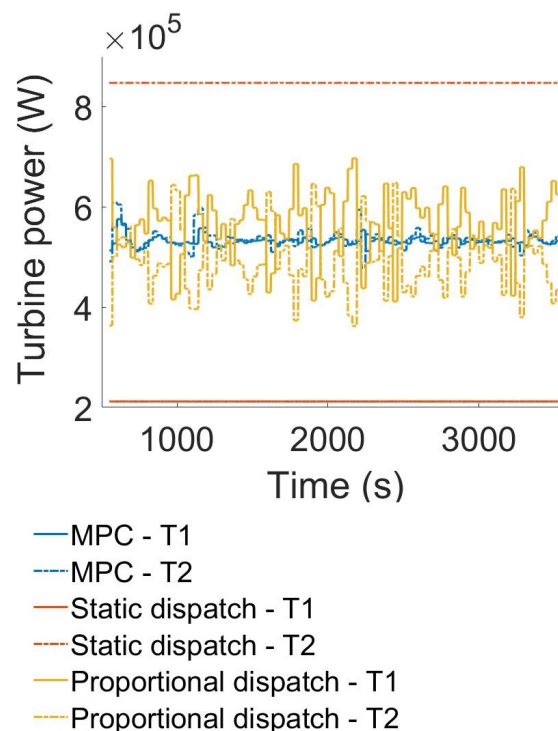

Figure 8. Dispatch of total, demanded power to the two turbine array.

The simulated total wind farm power, that is the sum power of the turbine array, is shown in Figure 9. It can be observed that for all, tested wind farm controllers the deviations from the power reference are within the Danish grid code limits [14]. With the PI-controller the normalized root mean square deviation from the power reference is 0.0083%. The normalized root mean square deviation during operation with the MPC is 2.3%. The deviation from the power reference is larger during operation with the MPC, since the MPC objective function trades off between power reference deviation and mechanical load reduction. The trade-off used in a real wind farm finally depends on the interests and needs of the wind farm operator.
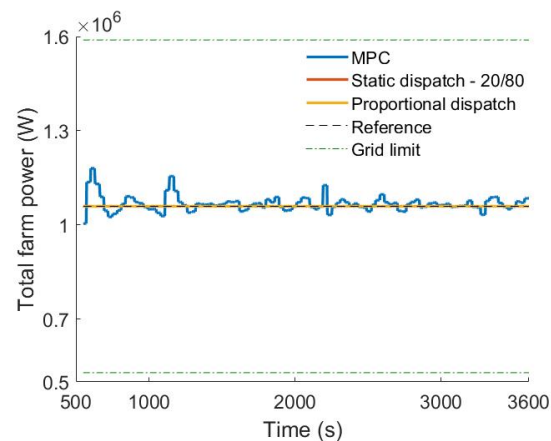
Figure 9. Wind farm controller performance in terms of power reference following ability.

Figure 10 shows the effect of the wind farm control approach on the tower bending moments of the turbines of the two turbine array. It can be observed that the bending moments during operation with the MPC are on average 16% smaller as compared to the proportional dispatch approach. The proportional dispatch shows larger equivalent moments mainly due to the larger variations of turbine power. The larger variations of power result in more fluctuations of a turbine's thrust force, and thus increase the turbine tower fatigue loads. During operation with the static dispatch approach the upstream turbine No. 1 shows 18% smaller fatigue loads than with the MPC. The downstream turbine No. 2, however, shows 85% larger fatigue loads than with the MPC. Thus, the sum fatigue loads of the two turbine array are smaller with the MPC than with the static dispatch.

Figure 11 shows the impact of the wind farm control approach on the sum equivalent tower bending moment of the two turbine array. Operation with the MPC shows the smallest, total, equivalent moment, which is 28% lower than under operation with the static dispatch approach and 16% smaller than under operation with the proportional dispatch approach. The MPC approach therefore successfully reduces turbine mechanical loads in this case study.
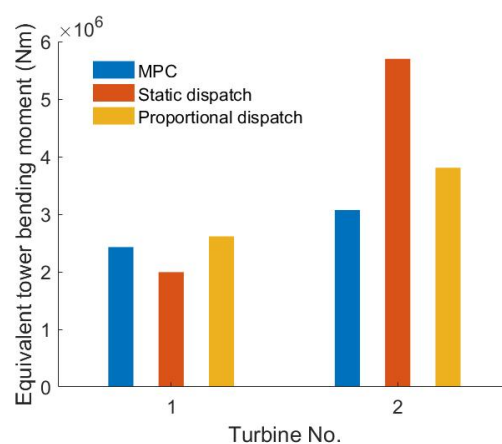

Figure 10. Effect of wind farm control approach on simulated, equivalent tower bending moment of turbines in two turbine array.
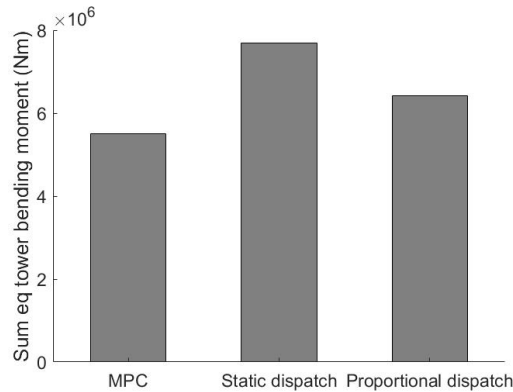
Figure 11. Impact of control approach on total wind farm fatigue loads.

4.4. Eight turbine case study

This case study aims at comparing the same controllers on an eight turbine array. Such eight turbine array is representative of a streamwise section of a typical offshore wind farm. The PI-controller again uses the proportional dispatch and static distribution dispatch functions. The static distribution is set for this case study as $\{f_1 = 0.22; f_2 = 0.19; f_3 = 0.17; f_4 = 0.14; f_5 = 0.11; f_6 = 0.08; f_7 = 0.06; f_8 = 0.03\}$. The choice of the distribution mimics a wind farm operators desire to manually dispatch turbines similar to their available power. It is close to the the available power in the nominal operation case, see 12, but slightly off, though without significant consequence for the purpose of this study, and exactly what wind farms operators would select as distribution factors is anyhow a guesstimate. The MPC targets a dispatch close to an equal distribution of turbine power set-points, as was used for the two turbine array. Since the turbine fatigue load model is derived for a two turbine array, it is however not given that an equal set-point distribution results in the lowest, possible fatigue loads for an eight turbine array.
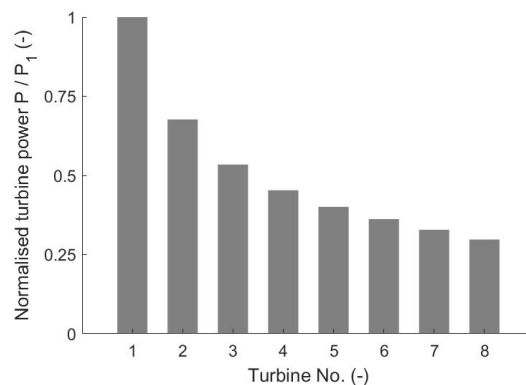

Figure 12. Distribution of turbine power in nominal operation. Turbine powers are normalized by power of upstream turbine.

Figure 13 shows the effect of the wind farm control approach on the tower bending moment of the turbines of the eight turbine array. It can be observed that the equivalent moments of the first, six upstream turbines increase with each successive downstream turbine due to larger turbulence intensity downstream. Under operation with the MPC, these six upstream turbines experience the lowest equivalent tower bending moment.
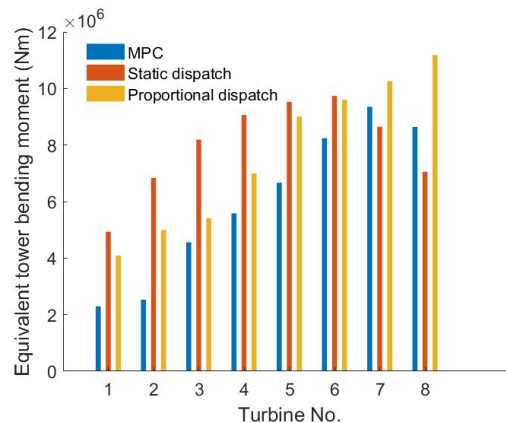
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Figure 13. Effect of wind farm control approach on simulated, equivalent tower bending moment of turbines in eight turbine array.

The lowest sum equivalent moments of all turbines are observed under operation with the MPC, as can be seen in Figure 14. Under operation with the MPC the sum equivalent moments are 25% lower than under operation with the static dispatch and are 22% lower than under operation with the proportional dispatch.
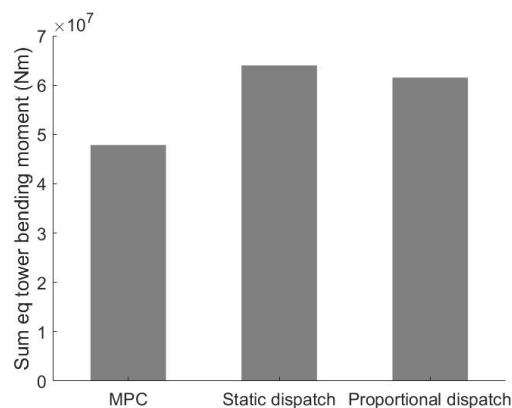

Figure 14. Impact of control approach on total fatigue loads of eight turbine array.

4.5. Main findings

The results of the case studies show that in the PI-controller the lack of knowledge on the effect of the power set-point distribution on turbine fatigue loads can result in less beneficial wind farm operation. In the present work such lack of knowledge of a wind farm operator results in up to 28% larger sum equivalent tower bending moments. The two case studies show that the model predictive wind farm control approach can reduce the sum equivalent tower bending moment as compared to commonly used wind farm control approaches. Moreover, the predictive nature of the MPC allows it to consider the future evolution of the wind speed at the turbines when deciding the most beneficial, future control actions. As such the controller takes the future available power at the wind turbines into account. Further, the effect of gusts on downstream turbines can be mitigated. More details on the mitigation of gusts shall be examined in future work.

5. Conclusion

The results of this work suggest that model-based wind farm control can reduce the sum of the equivalent tower bending moments of wind turbines in a wind farm during provision of ancillary services. The wind farm ancillary service defines the reference for the total wind farm power, which the wind farm controller aims to follow. Simulations of an eight turbine array show up to 28% lower sum equivalent tower moments during operation with the developed model-predictive controller. Commonly used wind farm controllers for provision of ancillary services lack knowledge of the effect of turbine operation on wind turbine fatigue loads. The observed 28% reduction of fatigue loads stems from the use of such knowledge in the developed model-predictive controller. Our future work focuses on the development of fatigue load models from higher fidelity aeroelastic simulation tools, analysis of the MPC control and investigation of the potential of the linear flow model for gust mitigation.

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