Model Predictive Wind Turbine Control with Move-Blocking Strategy for Load Alleviation and Power Leveling

U Jassmann¹, S Dickler¹, J Zierath², M Hakenberg¹, D Abel¹
¹ Institute of Automatic Control and Center for Wind Power Drives, RWTH Aachen University, 52056 Aachen
² W2E Wind to Energy GmbH, Strandstrasse 96, 18055 Rostock Germany
E-mail: u.jassmann@irt.rwth-aachen.de

Abstract. This contribution presents a Model Predictive Controller (MPC) with move-blocking strategy for combined power leveling and load alleviation in wind turbine operation with a focus on extreme loads. The controller is designed for a 3 MW wind turbine developed by W2E Wind to Energy GmbH and compared to a baseline controller, using a classic control scheme, which currently operates the wind turbine. All simulations are carried out with a detailed multibody simulation turbine model implemented in alaska/Wind.

The performance of the two different controllers is compared using a 50-year Extreme Operation Gust event, since it is one of the main design drivers for the wind turbine considered in this work. The implemented MPC is able to level electrical output power and reduce mechanical loads at the same time. Without de-rating the achieved control results, a move-blocking strategy is utilized and allowed to reduce the computational burden of the MPC by more than 50% compared to a baseline MPC implementation. This even allows to run the MPC on a state of the art Programmable Logic Controller.

1. Introduction

The enormous increase of rotor diameters and hub heights of wind turbines throughout the last 15 years [1] naturally causes higher loads, more flexible structures and hence higher material usage and costs. Therefore the demands on advanced, load reducing control systems have been rising constantly. Much research has been done in this area ranging from extended SISO or MIMO control loops [2–5], Individual Pitch Control [6–8], innovative actuators [9–12] and additional sensor information [13–16].

One promising approach for active load reduction on state-of-the-art wind turbines with or without additional actuators and measurements, is Model Predictive Control. This multiple input multiple output control approach has been studied by various authors [17–22], with focus on methods and their adaption to the given application. As these are extremely important aspects that provided many useful information to the authors, implementation details, especially regarding computational burden, have not been addressed so far.

In this paper we present a Model Predictive Controller (MPC) with move-blocking strategy for load alleviation and power leveling based only upon sensors available in state-of-the-art wind turbines. Compared to other control schemes, the MPC can actively consider constraints when
computing the control signals, which is especially important in extreme operation conditions as they need maximum allowable control actions. For future developments it is also advantageous that the MPC can easily incorporate wind predictions, although this aspect is not stressed in the presented work.

The performance of the MPC is evaluated by comparing the control results to the controller, which currently operates the wind turbine. For this, the 50-year extreme operation gust (EOG50) in all required conditions according to IEC61400-1 [23] is used.

The main contribution of this paper is the incorporation of a move-blocking strategy into the MPC, which reduces the computational burden compared to a baseline MPC implementation. This allows us to run the MPC and the Kalman-Filter in real-time on a state of the art Programmable Logic Controller (PLC) as used in the wind turbine prototype considered.

This paper is organized as follows. In section 2, a detailed alaska/Wind Multibody Simulation (MBS) model of the wind turbine considered is presented before the simplified wind turbine model used within the control system is introduced in section 3. In section 4, the MPC with move-blocking strategy is introduced. Simulation results regarding controller performance and computational burden will be discussed in section 5, before the paper is concluded in section 6.

2. Wind Turbine and Multibody Simulation Model
The wind turbine considered in this paper is the 3 MW W2E-120/3.0fc wind turbine, developed and manufactured by W2E Wind to Energy. The wind turbine combines a medium speed generator and a full converter system. The prototype of this wind turbine has been erected in Kankel, Mecklenburg-Western Pommerania (Germany) in 2013. The test site comprises a measurement mast to obtain the environmental conditions and the prototype which is equipped with several sensors available for model validation. The multibody model is implemented in alaska/Wind and comprises of the following submodels: foundation, tower, nacelle, yaw drive, pitch drive, rotor (hub and blades), drivetrain and generator. The drivetrain model comprises two masses, only coupled via a torsional spring-damper element, which is parametrized according to the first eigenfrequency of the drivetrain. The tower and the blades are modeled as beams, where the tower is reduced by the Craig-Bampton method and the blades by modal superposition techniques with respect to the first two modes in flap- and edgewise direction. In total the multibody model has 21 degrees of freedom. For this paper focuses on the control system, the reader is referred to [24–26] for further information on the MBS model and field test validation.

3. Simplified Controller Model
In this section a reduced-order model required for usage within the Extended Kalman Filter and the Model Predictive Controller is introduced and the relevant dynamics are compared to the MBS model.

3.1. Model-Structure and Baseline Equations
The reduced-order wind turbine model used throughout this work includes a flexible drivetrain model, comparable to [14, 27], which is described by:

\[ T_r = I_r \ddot{\phi}_r + d_{\Delta} \dot{\phi}_{rg} + c_{\Delta} \Delta \phi_{rg} \]  \hspace{1cm} (1)

\[-T_{g i_{gear}} = I_{g i_{gear}} \dot{\phi}_g - d_{\Delta} \ddot{\phi}_{rg} - c_{\Delta} \Delta \phi_{rg} \]  \hspace{1cm} (2)

with

\[ \Delta \phi_{rg} = \phi_r - \phi_g/i_{gear}. \]  \hspace{1cm} (3)
Thereby $T_r$ and $T_g$ denote rotor and generator torque, $i_{gear}$ gear ratio, $I_r$ and $I_g$ rotor and generator inertia. Rotor and generator position, speed and acceleration are denoted by $\phi_r$, $\dot{\phi}_r$, $\ddot{\phi}_r$, $\phi_g$, $\dot{\phi}_g$, $\ddot{\phi}_g$, and $\dot{\phi}_p$, $\ddot{\phi}_p$. Different from most available publications on MPC controlled wind turbines, e.g. [18, 27, 28], the reduced-order model in this work not only features the first tower eigenfrequency but additionally a collective first flap-wise rotor eigenfrequency, as proposed for controller design by Geyler [29] and also used within the MPC by Körber [19]. Compared to models without this collective first flap-wise movement the tower top acceleration is represented much better, since a step in the thrust force, i.e. pitch step, wind step, does not lead to a step in the tower top acceleration. Bear in mind that tower top acceleration usually also is a control variable. A schematic representation of the model is shown in Figure 1 and can be described by the following equations:

$$F_t - M_b R_{bs} \ddot{\phi}_b = M_t \ddot{X}_t + d_b \dot{X}_t + c_t X_t \quad (4)$$

$$F_t R_{td} - M_b R_{bs} \ddot{X}_t = M_b R_{bs}^2 \ddot{\phi}_b + d_b \dot{\phi}_b + c_b \dot{\phi}_b \quad . (5)$$

The input $F_t$ denotes the thrust force, $M_b$ and $M_t$ equivalent rotor and tower top mass, $c_t$ and $d_t$ tower spring and damper constants. $R_{bs}$ and $R_{td}$ denote the center of the rotor blade mass, the distance of the thrust force application point, $c_b$ and $d_b$ denote spring and damper coefficients of the torsional spring.

The control signal $T_g$ for generator torque is fed through the system directly, while the pitch velocity $\dot{\theta}$ is commanded to vary the pitch angle $\theta$.

The aerodynamic inputs, rotor torque $T_r$ and thrust force $F_t$, are described by the following well-known equations

$$F_t = 0.5 \rho \pi R_r^2 v^2 c_T(\theta, \dot{\phi}_r, v) \quad (6)$$

$$T_r = 0.5 \rho \pi R_r^2 v^3 \dot{\phi}_r^{-1} c_P(\theta, \dot{\phi}_r, v) \quad , (7)$$

with air density $\rho$, rotor radius $R_r$, effective wind speed $v$ and thrust and power coefficients $c_T$ and $c_P$. This results in a state space system with nine states, whereas the wind speed $v$ is included in the state vector as ninth state. No dynamic is assumed for this wind speed. An overview of the state space vector and the corresponding symbols can be found in Table 1.

Mechanical and electrical losses of the wind turbine are modeled as quadratic function of the electrical output power $P_{el}$ and the generator torque $T_g$, respectively. These losses are considered

| symbols |
| No. | in $X$ | in $x$ | description |
|------|--------|--------|-------------|
| 1    | $\phi_r$ | $\varphi_r$ | rotor speed |
| 2    | $\dot{\phi}_r$ | $\varphi_r$ | generator speed |
| 3    | $\Delta \phi_{rg}$ | $\Delta \varphi_{rg}$ | angular difference |
| 4    | $X_t$ | $\dot{X}_t$ | tower top position |
| 5    | $\dot{X}_t$ | $\ddot{X}_t$ | tower top velocity |
| 6    | $\phi_b$ | $\varphi_b$ | collective blade deflection |
| 7    | $\dot{\phi}_b$ | $\varphi_b$ | collective blade velocity |
| 8    | $\theta$ | $\vartheta$ | pitch angle |
| 9    | $v$ | $v$ | wind speed |

Table 1. Overview of systems states and corresponding symbols for the state vector $X$ of the non-linear system and the state vector $x$ for the linearized state space system.
as additional input torque $T_{loss}$ and can be described as:

$$P_{el-loss} = a_{el} \cdot P_{el}^2 + b_{el} \cdot P_{el} + c_{el} \quad (8)$$

$$P_{mec-loss} = a_{mec} \cdot T_g^2 + b_{mec} \cdot T_g + c_{mec} \quad (9)$$

$$T_{loss} = (P_{el-loss} + P_{mec-loss})/\dot{\phi}_g \quad (10)$$

This loss-related torque is added to the generator torque, such that the drivetrain is decelerated in the model.

![Figure 2. Input signals for wind speed, pitch angle and generator torque used for identification.](image1)

![Figure 3. Comparison of reduced-order model (orange) and multibody simulation model (blue).](image2)

### 3.2. Parameter Estimation and Validation

For identification and model comparison a baseline experiment was chosen, utilizing the available inputs wind speed $v$, pitch angle $\theta$ and generator torque $T_g$ to excite the system. The input signals are shown in Figure 2.

While drivetrain parameters can almost be used directly from the MBS model, the system parameters of the combined rotor-tower model are obtained by means of a least squares identification using simulation results of the detailed multibody simulation, which itself is fully validated against field measurements [26]. Values to be fitted are tower top and blade mass $M_t$ and $M_b$, thrust force application point $R_{bt}$, center of mass $R_{bs}$ as well as stiffness coefficients $c_b$, $c_t$ and damping coefficients $d_b$ and $d_t$ (for comparison see Figure 1). Initial values for those parameters can be derived from physical data. A least squares identification is conducted to obtain best-fitting parameters.

The comparison of the fitted reduced-order model and the MBS-model can be found in Figure 3. The tower top position of the reduced-order model does not match the position of the MBS model well. This is due to the model assumption made but not of high importance since the dynamic effects are of higher interest for the control task than the static. Tower top acceleration of the reduced-order model almost perfectly matches the acceleration predicted by the MBS model.
Compared with a fore-aft model only including the first tower eigenfrequency, the chosen model type reproduces the impact of wind and pitch angle steps more realistically.

4. Model Predictive Control with a Move-Blocking Strategy
In this section the implemented linear Model Predictive Controller shall be introduced. First the notation and linearization scheme of the reduced-order model, control and controlled variables and their scaling are presented. Before the move-blocking strategy is introduced, the baseline MPC formulation is given to define the general structure of the cost function and constraints.

4.1. Linearized Model, Control and Controlled Variables
To compute the linear MPC, the reduced-order model introduced in section 3 is linearized and discretized at each time step $T_{MPC}$. Different from all other publications on MPC controlled wind turbines known to us, here the model is not linearized at an equilibrium point, defined by the wind speed. The authors found that especially during extreme operation gusts, the actual operation point differs significantly from any equilibrium model. Therefore, the model is linearized at the currently active system state although it is not an equilibrium. In order to consider the systems inherent movement at this operation point the initial movement $\dot{X}_{k,OP}$ is included in the state space equation Eq. (11) as constant input.

Note that since this model is only valid close to the operation point linearized at, all variables (states, control and controlled variables) are denoted in lower case (for comparison see Table 1). The discretized, linearized model is written as

$$x_{k+1} = A_{Dk} x_k + B_{Dk} S_u u_k + E_{Dk} \dot{X}_{k,OP}$$

$$y_k = S_y C_{Dk} x_k + S_y D_{Dk} S_u u_k,$$  \hspace{1cm} (11)

with the system matrix $A_{Dk}$, input matrix $B_{Dk}$, output matrix $C_{Dk}$ and feed through matrix $D_{Dk}$. The matrix $E_{Dk}$ incorporates the initial derivative $\dot{X}_{k,OP}$. It is calculated identically as the input matrix $B_{Dk}$ when its continuous equivalent is an identity matrix. All those matrices are linearized and discretized at each time step $k$. The matrix $x_k$, $u_k$ and $y_k$ denote the state vector, the manipulated variables and the controlled variables, respectively. $S_u$ and $S_y$ are scaling matrices. The effective manipulated variables $u_{MPC}$ are defined as:

$$u_{MPC} = \begin{bmatrix} \dot{\phi}_{\text{max}}^{-1} \\ 0 \\ \Delta T_{g,\text{max}}^{-1} \cdot T_{MPC}^{-1} \end{bmatrix} \begin{bmatrix} \dot{\phi}_g \\ T_g \\ u_k \end{bmatrix} + \dot{X}_{k,OP}$$

$$y_k = \begin{bmatrix} \dot{\phi}_g^{-1} \cdot \text{rated} \\ 0 \\ P_{el,\text{rated}}^{-1} \end{bmatrix} \begin{bmatrix} \dot{\phi}_g \\ \dot{\phi}_g \\ T_g \end{bmatrix} + \begin{bmatrix} \ddot{x}_t \\ p_{el} \end{bmatrix}.$$  \hspace{1cm} (13)

The control variables are scaled by their maximum rate of change for easier comparison and weighting relative to one another. In the same fashion the controlled variables $y_{MPC}$, electrical output power $p_{el}$ ($P_{el} = \dot{\phi}_g \cdot T_g$), tower top acceleration $\ddot{x}_t$ and generator speed $\dot{\phi}_g$ are scaled to their rated values or to one.

4.2. Baseline Model Predictive Control
Generally spoken the MPC used in this work computes an optimal trajectory of control signal changes $\Delta u(\cdot | k)_{\text{opt}}$ by minimizing a cost function $J$:

$$\Delta u(\cdot | k)_{\text{opt}} = \arg \min_{\Delta u(\cdot | k)} J(\Delta u(\cdot | k))$$

$$J\left(\Delta u(\cdot | k)\right)$$  \hspace{1cm} (14)

$$\Delta u(\cdot | k)_{\text{opt}} = \arg \min_{\Delta u(\cdot | k)} J(\Delta u(\cdot | k))$$  \hspace{1cm} (15)
Variables denoted by \((\cdot |k)\) are vectors of predicted values from the time instance \(k\) over the complete horizon. The first value \(\Delta u_{\text{opt}}(k+1)\) of that control signal trajectory is added to the initial, absolute control signal \(U(k)\) and applied to the process at the next time instance \(k+1\), such that

\[
U(k+1) = U(k) + \Delta u_{\text{opt}}(k+1 |k)
\]

holds. The cost function \(J\) is of the following form

\[
J = \sum_{i=0}^{N_2} \|y(k+i |k) - y_{\text{ref}}(k+i |k)\|_Q^2 + \lambda \sum_{i=0}^{N_u} \|\Delta u(k+i |k)\|_R^2 + \|u(k+i |k)\|_S^2 \quad (17)
\]

whereas the controlled variables \(y(\cdot |k)\) are compared to their reference \(y_{\text{ref}}(\cdot |k)\) for each point within the prediction horizon \(N_2\). The control signal \(u(\cdot |k)\) can be altered at each time instance \(k\) within the control horizon \(N_u\). This cost-function is subject to the system dynamics

\[
y(k+i |k) = S_y C_{Dk} x(k+i |k) + S_y D_{Dk} S_u u(k+i |k)
\]

\[
x(k+i |k) = A_{Dk} x(k+i-1 |k) + B_{Dk} S_u u(k+i-1 |k) \quad (18)
\]

with \(u(k+i |k) = \sum_{j=0}^{i} \Delta u(k+j |k)\)

as well as control and state constraints of the form

\[
\Delta u_{\text{min}} \leq \Delta u(\cdot |k) \leq \Delta u_{\text{max}}
\]

\[
U_{\text{min}} - U_0 \leq u(\cdot |k) \leq U_{\text{max}} - U_0
\]

\[
A_c x(\cdot |k) \leq b_c \quad (19)
\]

The control signals constraints limit the pitch rate to \(12^\circ/s\) and the generator change rate to \(\pm 45 \text{kNm}\). Furthermore the generator speed, the pitch angle and the electrical output power are subject to constraints. The generator speed is limited to \(590 \text{rpm}\), the pitch angle has to remain between \(-5^\circ\) and \(90^\circ\) and the electrical output power shall not exceed \(3.15 \text{MW}\). The MPC used in this work is run every \(T_{MPC} = 100 \text{ms}\). The prediction horizon should be chosen such that the lowest dynamic of the system controlled can be fully captured \([30]\). In case of a wind turbine the lowest dynamic is the tower fore-aft movement with an eigenfrequency of approximately \(0.28 \text{Hz}\). Therefore the prediction horizon \(N_2\) is chosen to be \(50 \text{ (5s)}\). For the control horizon \(N_u = 10 \text{ (1s)}\) was found to be a suitable choice. Similar values can be found in comparable publications which also consider the tower within the simplified MPC model \([18,19,28]\).

4.3. **Move-Blocking Strategy**

As stated before, the MPC is run in a \(10 \text{Hz}\) task. This is reasonable looking at the dynamic behavior e.g. of the drivetrain and occurring wind variations. At the same time the prediction horizon \(N_2\) has to be long enough to capture tower and rotor dynamics. As a consequence the control horizon \(N_u\) tends to be rather long as shown in Figure 4. In general such a constellation causes high computational burden. In order to reduce that computational burden and to ease the parametrization, an MPC with a move-blocking strategy can be used. The concept proposed here is similar to the concept introduced in \([31]\). There it is called a ‘multirate prediction horizon’. The concept proposed there is a move-blocking strategy for the controlled variables \(y(\cdot |k)\). In this work this is extended, such that also the manipulated variables \(\Delta u(\cdot |k)\) can only be altered at defined but not necessarily equally distributed points within the horizon and
are assumed constant in between those points. This can reduce the number of samples within $N_u$ and hence reduce the complexity of the optimization problem and by that the computational burden significantly, as also shown in a more theoretically manner in [32, 33].

Limiting the number of allowed control actions within the control horizon can reduced the computational burden drastically. With respect to the dynamics considered (drivetrain and rotor-tower-system) it was found that three high frequent control actions at the beginning of the horizon combined with only two more control actions at step 5 and $N_u$ are enough to first control drive train dynamics (rotor speed) and in the second place reduce fore-aft movements.

The explained principle of the MPC with move-blocking strategy is now to be included in the baseline MPC framework introduced before. For easier notation Eq. (17) is rewritten in vectorized form:

$$J = (y(\cdot|k) - y_{ref}(\cdot|k))^T Q (y(\cdot|k) - y_{ref}(\cdot|k)) + \lambda \left( \Delta u(\cdot|k)^T R \Delta u(\cdot|k) + u(\cdot|k)^T S u(\cdot|k) \right).$$

Thereby the weighting matrices $Q$, $R$ and $S$ are diagonal repeated versions of $Q_i$, $R_i$ and $S_i$ of Eq. (17). Necessarily the output and reference trajectories are sampled equally and the control signals $u$ and $\Delta u$ are changeable at the same points. For usage within the MPC with move-blocking strategy, these trajectories have to be redefined as:

$$y^*(\cdot|k) = \begin{bmatrix} y^*(k + \nu_1 | k) \\ y^*(k + \nu_2 | k) \\ \vdots \\ y^*(k + \nu_L | k) \end{bmatrix}, \quad u^*(\cdot|k) = \begin{bmatrix} u^*(k + \zeta_1 | k) \\ u^*(k + \zeta_2 | k) \\ \vdots \\ u^*(k + \zeta_E | k) \end{bmatrix},$$

whereas the output and reference trajectories are summarized as $y^* (\cdot | k)$ and all control signals are summarized as $u^*$. The indices $\nu_i$ and $\zeta_i$ correspond to the points within the horizon $N_2$.

Figure 4. Illustrative example for different system dynamics considered within one MPC and the use a move-blocking strategy.
and $N_u$, respectively, to be evaluated and are defined by:

$$\nu = [\nu_1, \nu_2, \cdots, \nu_L]^T \quad \text{with} \quad 0 < \nu_i < N_2 \quad \text{and} \quad L \leq N_2$$

$$\zeta = [\zeta_1, \zeta_2, \cdots, \zeta_E]^T \quad \text{with} \quad 0 < \zeta_i < N_U \quad \text{and} \quad E \leq N_u$$

When $L = N_2$ and $E = N_u$ is chosen it again is the baseline MPC formulation.

5. Simulation Results

For evaluation of the controller performances, a 50-year Extreme Operation Gust (EOG) close to rated wind speed is used. For the wind turbine considered in this paper, this event is crucial for dimensioning. According to IEC61400-1 [23], it has to be repeated for four different rotor positions from $0^\circ$ to $90^\circ$ and horizontal wind inflow directions of $\pm 8^\circ$. Both the baseline and the Model Predictive Controller are tested with the multibody simulation. The MPC is operated in combination with an Extended Kalman Filter for state estimation, rather then perfect knowledge about the system’s states. This estimation also includes an estimation of the wind speed, such that the wind speed plotted in the following figures, is not identical to the wind speed used to linearize the models and compute the prediction.

The controller currently used to operate the wind turbine and for comparison throughout this section does include a drive train damper as well as a power and speed regulator. It does not include a tower damper or an individual pitch controller.

![Figure 5](image_url)

**Figure 5.** Simulation results for an 50-year Extreme Operation Gust. Blue graph shows all results for the classic controller being activated and orange the results when the MPC is used for wind turbine control.
Figure 6. Simulation results for an 50-year Extreme Operation Gust. Blue graph shows all results for the classic controller being activated and orange the results when the MPC is used for wind turbine control.

5.1. Simulation Results
The wind turbine behavior when operated with the different controllers is plotted in Figure 5 and Figure 6. Regarding the loads, the tower top acceleration can be reduced by more than 50% when the MPC is used compared to the baseline controller. This is to expect, since tower top acceleration is one of the MPC’s control goals. Furthermore the tower bottom bending moment shown in Figure 5 d) can be slightly reduced in its maximum values. Also, both values settle faster when the MPC is activated. In Figure 5 c), the flapwise blade root bending moment is plotted. The gap between maximum and minimum loads shows why this test is repeated in different conditions. A significant reduction of the maximum bending moment was not achieved here, however a fast settling of the system was. This is mainly due to the fact that no wind prediction is considered, but a pure wind estimation. Therefore the control cannot react quickly enough at the very beginning of the gust, where loads are the highest.

Additionally to the achieved load reduction, with MPC being activated it is also possible to reduce the electrical output power fluctuation from 8% to only 4% maximal deviation from the reference power, which is shown in Figure 6 d). This comparison only includes the section until 16 s, since from that point on a reference change of the supervisory control interferes with the classic controller. Also important to note is, that the control action of the MPC is not significantly higher than that of the classic controller. In fact the pitch’s change rate is even slightly less with MPC.
5.2. Computational Results
While simulation results regarding loads and power output of the baseline MPC and the MPC with a move-blocking strategy are almost identical, the computational burden differs significantly. To only get an indication for the reduction of the computational burden, the amount of time spent computing the MPC compared with the rest of the simulation is analyzed. Figure 7 shows the portions different parts of the simulation have in the overall computational time taken. The simulation and some overhead functionality (including activated plot and data-storage functions) by far account for most of the computational time needed. The MPC itself only accounts for 13% in case of the baseline MPC. When the move-blocking strategy is activated, the share of the MPC is reduced to only 6%, so a reduction of 50% is easily achievable.

![Figure 7. Distribution of the computational time required for a system simulation.](image)

The hardware planned to be installed in the considered wind turbine is a state of the art Programmable Logic Controller (PLC), a MC210 of Bachmann Electronic. Using Bachmann’s M-target® and Mathwork’s Simulink Coder® the MPC can be compiled, downloaded and run on that hardware without additional programming. While it was not possible to run the baseline MPC on that PLC, since the computational time required was higher then allowed, with activated move-blocking strategy the MPC could be run on this hardware and provided the exact same results as in pure simulation. Nonetheless the turnaround time was still too high with 60 ms. Since no other code optimization etc. has been performed yet, the authors see the potential to further reduce that time, to integrate the MPC in the complete control system of the wind turbine and to run real-time tests.

6. Summary and Conclusion
In this paper we presented a MPC for load reduction and power leveling which in general showed good results for the EOG50 load. Since no wind prediction was used, the blade root bending moments are reduced as much as desired. The move-blocking strategy has proved to be a suitable tool to significantly reduce computational burden caused by the MPC, while at the same time control results are not derated.

Since the whole code for the MPC, model composition and linearization is not optimized yet, the authors expect further time savings in future. Next steps will involve further code optimization in order to allow for real-time Hardware-in-the-Loop tests.

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