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Nonlinear Model Predictive Control of Floating Wind Turbines

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ABSTRACT

In this work a nonlinear model predictive control method for a floating wind turbine is presented. A reduced nonlinear model including disturbance preview of wind and waves is derived and implemented to compute optimal input trajectories for collective pitch and the generator torque. A cost functional is introduced which fulfills all desired constraints and controller goals for above rated wind conditions. The controller is tested for extreme and fatigue load cases and a significant reduction of the power and rotor speed deviations is obtained. Furthermore, ultimate tower loads and damage equivalent loads on shaft and blades are decreased. Although more detailed testing is necessary, this preliminary results show the advantages of nonlinear model predictive control for floating wind turbines.

KEYWORDS

floating wind turbine control; nonlinear model predictive control.

INTRODUCTION

Floating wind turbines offer the prospect of harvesting offshore wind energy at deep water locations. Platform motions render a system's behavior much more dynamic compared to onshore turbines and thus demanding high requirements on the control system. Particularly for blade pitch control new concepts have to be devised to regulate the rotor speed and reduce structural loads in the presence of a low frequency pitch motion of the floating platform. The benefit of including disturbance information in an optimization process of a Nonlinear Model Predictive Controller (NMPC) has been shown in previous work (Körber and King, 2011; Schlipf et al., 2012b; Schuurmans et al., 2013) for onshore turbines. First field tests by Schlipf et al. (2012a) and Scholbrock et al. (2013) show that LIDAR systems are able to provide useful preview information for feedforward control. Additional to the wind disturbance, offshore floating turbines are also disturbed by waves, often not aligned with the main wind direction. Buoys or special lidar systems could estimate the height of the incoming wave acting on the floating turbine. This additional information paves the way to apply NMPC also to floating wind turbines.

Finding the right control strategy for offshore floating wind turbines has been an important topic since the beginning of floating wind turbines research. The interaction between the pitch controller and the platform motion is not well or even negative damped, as pointed out in many publications, see (Jonkman, 2007; Butterfield et al., 2007; Larsen and Hanson, 2007; Withee, 2004). Wayman and Sclavounos (2006) also mentioned the coupling in her analysis of the dynamics of a floating wind turbine. For floating wind turbines the goals for the controller have to be adjusted as mentioned by Larsen and Hanson (2007) and Lindeberg (2009) to guarantee stability of the system. The coupling comes from a complex pair of non-minimum phase zeros as described by Fischer (2012). They are located near the low natural frequency of the platform pitch mode. There are several methods how to deal with this coupling and how to guarantee stability of the system. A straightforward approach is to lower the closed-loop bandwidth of the pitch controller under the platform pitch frequency as done by Jonkman (2007) and Larsen and Hanson (2007). But, as mentioned by Larsen and Hanson (2007), this results in a rotor overspeed up to 30%. An alternative method using a stall controller is also mentioned by Larsen and Hanson (2007) and Nielsen et al. (2006). In the latter patent an estimator-based controller is proposed which basically tries to estimate the actual wind velocity excluding the tower movement. With this knowledge the change of turbine speed resulting from the tower movement is hidden for the controller and a negative damping is avoided. Another approach is to use gain scheduling as mentioned by Lindeberg (2009). An important disadvantage in gain scheduling is that stability cannot be guaranteed. Nielsen et al. (2012) propose an approach in which a basic pitch controller is augmented by an increment pitch angle controller.

There are also several approaches in model based control for floating wind turbines like the LQ approach in (Lindeberg, 2009), the MPC approach in (Henriksen, 2011), the compensation of non-minimum phase zeros in (Fischer, 2012) or the variable power collective pitch approach in (Lackner, 2012). Furthermore, Namik and Stol (2010) used an periodic state space controller to control the individual blade pitch and Magar et al. (2013) showed that it is promising to include knowledge of disturbances into the controller design. Based on these considerations, the NMPC approach, in which a model with state and load restrictions and disturbance previews are included, seems to be a technique with good prospects. In the following a NMPC for floating wind turbines is introduced, which uses the preview of the rotor effective wind speed and the wave height to control a floating turbine in a mathematically optimal way. The main purpose of this paper is to estimate the potential of this control strategy.

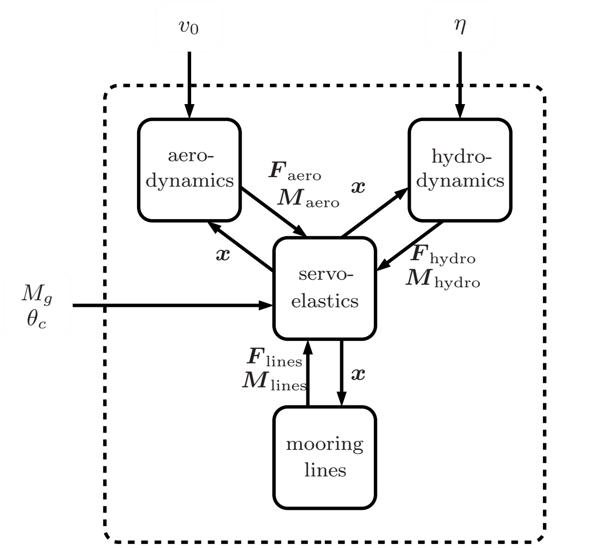

Figure 1: *Control and disturbance inputs to the submodules of the reduced internal model.*

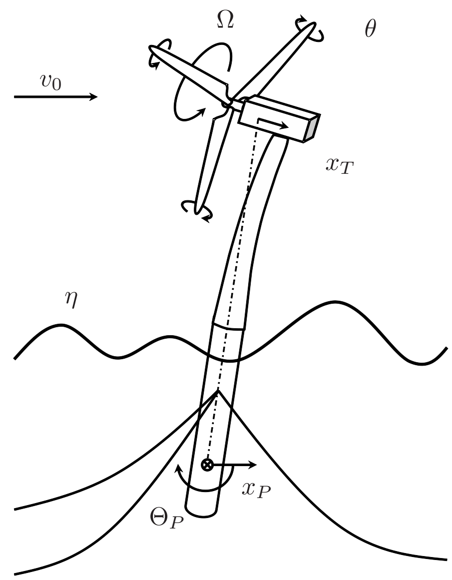

Figure 2: *Considered DOFs and disturbances of the reduced internal model.*

MODELING

For this study a 5 MW turbine on a spar-buoy is used (Jonkman, 2007) and implemented in the coupled aero-hydro-servo-elastic simulation tool FAST (Jonkman and Buhl, 2005). This high-fidelity model is used for simulations, whereas a reduced model is incorporated in the controller to foresee future plant behavior and, thus, calculate the optimal actuator action.

Full Simulation Model

The coupled FAST model for the floating wind turbine system consists of a flexible multibody system which experiences external forces from aerodynamics, hydrodynamics and mooring system. These are calculated in dedicated submodules of the code. The structural model represents dynamics of flexible parts up to the second mode. A second order linear model is added for the collective pitch actuator, resulting in a total of 22 degrees of freedom (DOFs). The hydrodynamic model is based on linear potential flow theory with the damping term of Morison's equation to account for viscous effects. The frequency-dependent solutions to the separated radiation and diffraction problem are solved in a preprocessing step by a hydrodynamic panel code. During the simulation, the pre-calculated fluid velocity and accelerations on several strips along the platform act as disturbance inputs to the hydrodynamic subsystem. In the aerodynamic subsystem the disturbance inputs are the components of a turbulent three-dimensional wind field on several grid points over the rotor disk. With these inputs aerodynamic forces are calculated applying BEM (Blade Element Momentum) theory. The floating spar-buoy is anchored over three slack mooring lines attached at fairleads below the center of buoyancy. Horizontal and vertical forces at the fairleads are calculated by solving iteratively a quasi-static equation for a slack line. The described model has proven reliable accuracy which justifies its application as full simulation model to validate the NMPC based on the reduced internal model.

Reduced Internal Model

The reduced model features several simplifications in a way that it still reproduces reliably the overall dynamic behavior of the system. From a numeric point of view focus is set on computational speed in order to cope with real-time requirements. Therefore, iterations, recursions, integrations, time-to-frequency domain conversions, excessive memory access, etc. is avoided wherever possible. Its main features and derivation are given in (Sandner et al., 2012). The validity of this model and its applicability for a large series of design load case simulations are shown by Matha et al. (2012). Similar to FAST, the reduced model is divided into four submodules: The servo-elastic, aerodynamic, hydrodynamic and the mooring line subsystem, see Figure 1.

Reduced Servo-Elastic System

The structure is modeled as a coupled nonlinear multibody system of the $p = 4$ rigid bodies: platform, tower, nacelle and rotor. Due to the considered control problem only $f = 4$ DOFs are considered as illustrated in Figure 2. Major internal forces and displacements like platform motion, rotor speed, blade pitch angle and tower top displacement show good agreement with the full simulation model whereas load distributions or specific node deflections of certain bodies are not sought to be covered. The simplification implies, however, that higher frequency modes of the stiffer DOFs like the blades or generator shaft are not considered. The minimal set of allowed body motions has been found to be optimal for the function as internal model. The DOFs are comprised in vector $\boldsymbol{q}$ as

$$\boldsymbol{q} = \begin{bmatrix} x_P \\ \Theta_P \\ x_T \\ \Omega \end{bmatrix}, \tag{1}$$

where x_P is the displacement of the platform's center of mass, Θ_P is the platform pitch angle, x_T is the tower top displacement and Ω is the rotor speed. The equations of motion of the 3D model are set up by applying the Newton-Euler formalism for holonomic systems. Newton's Second Law as well as Euler's law is set up for each body in all spacial directions. The global Jacobian Matrix $\boldsymbol{J}$ allow a generalized description for all bodies. It remains according to Schiehlen and Eberhard (2012) a $(2 \cdot 3p)$-dimensional system of equations

$$\boldsymbol{M} \cdot \boldsymbol{J}(\boldsymbol{q}) \cdot \ddot{\boldsymbol{q}} + \boldsymbol{k}(\boldsymbol{q}, \dot{\boldsymbol{q}}) = \boldsymbol{p}(\boldsymbol{q}, \dot{\boldsymbol{q}}) + \boldsymbol{Q}(\boldsymbol{q}) \cdot \boldsymbol{g}(\boldsymbol{q}, \dot{\boldsymbol{q}}), \qquad (2)$$

with the global square mass matrix $\boldsymbol{M}$ and the distribution matrix $\boldsymbol{Q}$. Coriolis-, centrifugal and gyroscopic forces and resulting moments are contained in $\boldsymbol{k}$, external forces and moments in $\boldsymbol{p}$, including the generator torque M_g, and reaction forces and moments in $\boldsymbol{g}$. According to the Lagrangian principle $\boldsymbol{g}$ is always pointing into constrained directions and is eliminated by multiplying Equation (2) by $\boldsymbol{J}^T$ from the left. The resulting coefficient of the acceleration term remains as the $(f \times f)$ mass matrix $\tilde{\boldsymbol{M}}$ after the transformation, whereas the vectors $\boldsymbol{k}$ and $\boldsymbol{p}$ of Equation (2) result in vectors $\tilde{\boldsymbol{k}}$ and $\tilde{\boldsymbol{p}}$. The coupled system can then be written in state-space formulation as

$$\dot{\boldsymbol{x}} = \begin{bmatrix} \dot{\boldsymbol{q}} \\ \ddot{\boldsymbol{q}} \\ \dot{\theta} \\ \ddot{\theta} \end{bmatrix} = \begin{bmatrix} \dot{\boldsymbol{q}} \\ \tilde{\boldsymbol{M}}^{-1}(\boldsymbol{x}) \cdot \left(\tilde{\boldsymbol{p}}(\boldsymbol{x}) - \tilde{\boldsymbol{k}}(\boldsymbol{x})\right) \\ \dot{\theta} \\ \omega^2\theta_c - 2\xi\omega\dot{\theta} - \omega^2\theta \end{bmatrix}, \qquad (3)$$

where θ_c is the collective blade pitch control input, ω the undamped natural frequency, and ξ the damping factor of the pitch actuator. The latter Equation (3) is written via symbolic programming and, thus, can be directly compiled, yielding high computational efficiency. The external forces and moments of $\boldsymbol{p}$ need to be computed by separate models which are explained in the following.

Reduced Aerodynamics

Aerodynamics are based on a polynomial fit to look-up data for the power and thrust coefficients that is gained in a preprocessing step. Aerodynamic coefficients allows the calculation of rotor torque and thrust with only a scalar rotor effective wind speed v_0, that can be extracted from a three-dimensional wind field. Compared to the aerodynamic BEM model implemented in the full reference model, the reduced model saves major computational time and still shows good agreement, see (Schlipf et al., 2012b). The platform pitch Θ_P and the tower top velocity $\dot{x}_T$ are considered for the wind speed relative to the rotor.

Reduced Hydrodynamics

Hydrodynamic forces are computed by the reduced model through a potential flow approach. Morison's equation is the basis for the development of a wave load estimation which requires only the current wave elevation η as disturbance input, which can be obtained from a simulation with FAST. Eventually, kinetics of wave-structure interaction can be calculated without a numerical integration over depth due to the applied deepwater approximation for linear waves. This method of disturbance reduction has been implemented and evaluated in detail by Sandner et al. (2012).

Reduced Mooring Line System

Quasi-static fairlead forces from the mooring lines as a function of horizontal and vertical displacements are calculated offline, fitted to a polynomial curve, which is evaluated during runtime.

CONTROLLER DESIGN

In this section, the NMPC is derived using the wind speed and wave height preview information. It is based on (Schlipf et al., 2012b). In this work, the NMPC is designed for all wind conditions above rated wind speed.

Problem Definition

NMPC is an advanced control tool which predicts the future behavior of a system using a nonlinear internal model and the current measurements. With this information, the control actions necessary to regulate the plant are computed by solving an optimal control problem over a given time horizon. Part of the solution trajectory for the control inputs is transferred to the system, new measurements are gathered, and the optimal control problem is solved again at the next time step. Feedback is incorporated, since the current state of the turbine is implemented as the initial condition of the optimal control problem (Findeisen, 2005) at the next time step. Multivariable control and constrains on actuator and states are incorporated in the optimization.

The considered optimal wind turbine control problem can be described as follows. The objective is to find the optimal control trajectory $u(\,\cdot\,)$ in the presence of the disturbance $d(\,\cdot\,)$, minimizing the cost functional J_{OCP}. It is defined as the integral over the time horizon T_{final} of the objective functional F from the actual time t_0 to the final time $t_0 + T_{\text{final}}$, with the reduced nonlinear model and the set of constraints H:

$$\begin{aligned} &\min_{u(\,\cdot\,)} \; J_{OCP} \\ \text{with:}\;\; & J_{OCP} = \int_{t_0}^{t_0+T_{\text{final}}} F(x(\tau), u(\tau), d(\tau))d\tau, \\ \text{s.t.:}\;\; & \dot{x} = f(x, u, d) \\ & x(t_0) = x_0 \\ & H(x(\tau), u(\tau), d(\tau)) \geq 0 \quad \forall \tau \in [t_0, t_0 + T_{\text{final}}]. \end{aligned} \qquad (4)$$

The crux of designing the NMPC is to translate the verbal formulation of the control goal to a mathematical formulation of F and H. The optimal control goal can be stated as "minimizing the loads above rated wind speed without decreasing the energy production". In classic wind turbine control Burton et al. (2001), this is in general done by limiting rotor speed and power above the rated wind speed.

The objective functional should be quadratic for computational reasons. This implies the weights to be independent of the system states and inputs, but they are allowed to be dependent on external disturbances. Here, F is chosen to

$$\begin{aligned} F(x(\tau), u(\tau), d(\tau)) = \;\; & Q_1 && (\Omega(\tau) - \Omega_{rated})^2 \\ + \;\; & Q_2 && \dot{x}_T^2(\tau) \\ + \;\; & Q_3 && (P_{el}(\tau) - P_{rated})^2 \\ + \;\; & Q_4 && \dot{\Theta}_P^2(\tau) \\ + \;\; & R_1(v_0(\tau)) && \dot{\theta}^2(\tau) \\ + \;\; & R_2 && \dot{M}_g^2(\tau). \end{aligned} \qquad (5)$$

The first line of (5) penalizes the deviation from the rated rotor speed, and in the second line the tower fore-aft velocity is penalized to minimize loads on the tower. The third line is necessary to maintain rated power P_{rated} and the forth line is used to decrease the pitch movement of the floating platform. The weight $R_1(v_0(\tau))$ (see Figure 3) is designed to penalize the blade pitch actuator rate. The static blade pitch angle over static wind speed $\theta_{ss}(v_{ss})$

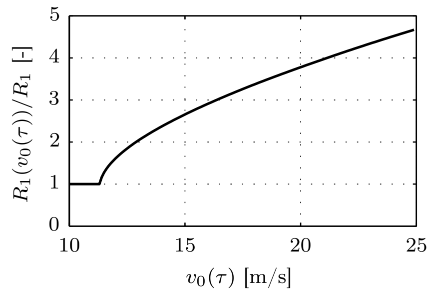

Figure 3: *Normalized weight of the pitch rate.*

is used to account for the higher sensitivity of the blade pitch at higher wind speeds, together with the gain correction factor $GK(\theta)$ from (Jonkman et al., 2009) and the static weight R_1:

$$R_1(v_0(\tau)) = R_1/GK(\theta_{ss}(v_0(\tau))). \tag{6}$$

The weight R_2 is used to limit the activity of the generator torque M_g.

The set of constraints H, which can be organized in the form $H \geq 0$, is chosen as

$$\Omega(\tau) \leq 1.2\ \Omega_{rated} \tag{7a}$$
$$\theta_{min} \leq \theta(\tau) \leq \theta_{max} \tag{7b}$$
$$\left|\dot{\theta}(\tau)\right| \leq \dot{\theta}_{max} \tag{7c}$$
$$|M_{yT}(\tau)| \leq M_{yT,max}. \tag{7d}$$

The constraint (7a) limits the rotor speed to 120% of Ω_{rated}, (7b) limits the pitch angle to its feasible positions, (7c) constrains the pitch rate to $\dot{\theta}_{max}$ and (7d) limits the tower fore-aft bending moment to $M_{yT,max}$ which can be chosen according to the wind turbine design. The first three constraints are implemented as hard constraints, (7d) as soft constraints into the objective functional (5).

Problem Solving

The optimal control problem is converted by the Direct Multiple Shooting method (Findeisen, 2005) into a nonlinear program. Here, the control inputs are discretized in K piecewise constant stages, see Figure 4. The ODEs of the model are solved numerically on each interval. The optimization is performed over the set of initial values for all states and the control outputs. Additional constraints are applied to ensure that the states at the end of each stage coincide with the initial conditions of the subsequent stage. This method gives significant improvements over the Direct Single Shooting approach, especially with respect to numerical stability.

The nonlinear program can be solved with Sequential Quadratic Programming (SQP) and shooting is repeated. The separation of the optimization problem into multiple stages results in a faster solution due to the better approximation of the Lagrangian Hessians of the nonlinear problem parts in each stage by low rank updates (Franke, 1998).

Here, Omuses (Franke, 1998) is used as a front-end to the large-scale SQP-type nonlinear optimization solver HQP. The prediction horizon is set to $T_{\text{final}} = 5$ s and the time steps to 0.2 s, resulting in $K = 25$ stages. Those values are chosen heuristically: 5 s is a realistic minimal preview time of a LIDAR system (Schlipf

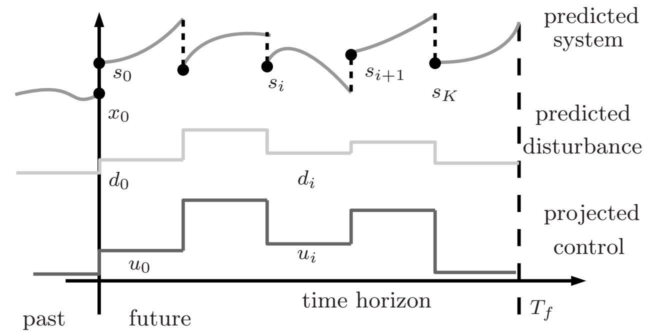

Figure 4: *Principle of the direct multiple shooting method.*

et al., 2012b) and in the magnitude of a typical wave period time T_p. The time steps are chosen to be close to a typical LIDAR update rate. The differential equations are solved with a fourth-order explicit Runge Kutta method with fixed step size.

The proof of closed-loop stability of a nonlinear and constrained system solved by a model predictive controller is beyond the scope of this work and is fairly complex, but the following results will show that there is no evidence of any stability problem in this case.

Considerations for Real Applications

There are two main issues which have to be considered for an implementation of the presented NMPC. An intermediate result can be far away from the optimum due to the Direct Multiple Shooting method. The presented approach leads to the iterative solution of a non-convex optimization problem and, thus, there is no guarantee to find the global minimum in the allotted time slot. Figure 5 depicts a histogram of the time needed to execute one optimization. Here, the optimization is repeated at every 0.2 s. Since the mean NMPC processing time is 1.11 s, the test setup is not capable for real-time computation, yet.

Furthermore, in this early stage of development it is assumed that all states are perfectly measured. As a next step it is necessary to implement different estimators, e.g. a disturbance estimator for wind and wave forecasting using LIDAR and buoyage data. In addition, a sensor concept for measuring attitude and position of the floating platform is another object of research. Possible sensor types are accelerometers, GPS receivers, (fiber optic) gyroscopes, magnetometers or other sensors e.g. used in aviation or naval architecture.

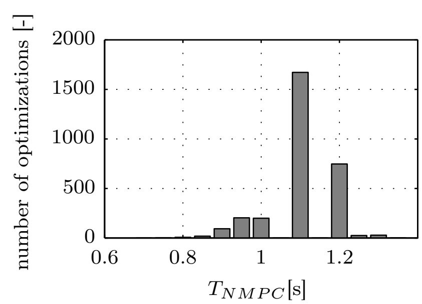

Figure 5: *Histogram of the time used by the NMPC to find the optimal solution.*

Table 1: *Maximum values of the extreme load simulations.*

	BC	NMPC	NMPC/BC
$\Delta\Omega$ [rpm]	1.59	0.22	14 %
M_{yT} [MNm]	110	85	77 %
M_{LSS} [MNm]	4.77	4.27	90 %

SIMULATION RESULTS

In this section the NMPC is compared to a baseline controller (BC) based on the work of Larsen and Hanson (2007) and Jonkman (2007): The BC is an adaptation of the onshore baseline controller (Jonkman et al., 2009) with reduced gains of the PI pitch controller to avoid negative damping. The generator torque is held constant above rated wind speed.

Extreme Loads

In a first step the NMPC is compared to the baseline controller regarding its reaction to gusts. The disturbances are created according to the Design Load Case (DLC) 2.3 from current standards (IEC61400-3): Irregular waves with significant wave height of $H_S = 2.73$ m and a peak spectral period of $T_p = 8.92$ s are used. The hub-height wind is a time series with an extreme operation gusts (EOG) at $v_{rated} + 2$ m/s $= 13.4$ m/s. The simulations are done with the full aero-hydro-servo-elastic model without the electrical fault of DCL 2.3 to concentrate on the control behavior. The wind speed v_0, the wave height preview η and the peak spectral period T_p as well as all states $\boldsymbol{x}$ are directly fed into the NMPC assuming perfect measurements and estimation.

Figure 6 and Table 1 compare the pitch angle θ, generator torque M_g, platform pitch Θ_P and platform displacement x_P, tower top displacement x_P, rotor speed Ω, low speed shaft torque M_{LSS} and tower base fore-aft bending moment M_{yT} for the different controllers. The NMPC adjusts both the pitch angle and the generator torque and is able to minimize rotor overspeed and loads. Although there are significant changes in the generator torque, the maximum value of the low speed shaft torque M_{LSS} can be decreased. Due to the capability of the NMPC to constrain states, the tower for-aft bending moment is limited to $M_{yT,max} =$ 85 MNm. The limit is implemented as a soft constrain tolerating a slight exceeding.

Fatigue Loads

In a second comparison the NMPC is evaluated regarding its behavior in turbulent wind conditions. For this purpose a turbulent wind field with mean wind speed of 16 m/s and a turbulence intensity of 15.4% is used for the full simulation model. The rotor effective wind is extracted from the windfield (see (Schlipf et al., 2012b) for details) and integrated in the preview of the NMPC. According to DLC 1.1, irregular waves with significant wave height of $H_S = 3.37$ m and a peak spectral period of $T_p = 10.1$ s are applied.

Figure 7 and Table 2 depict that with the chosen set of parameters the NMPC is able to significantly reduce the standard deviation $\sigma(\Omega)$ of the rotor speed and $\sigma(P)$ of the electrical power. This decrease is mainly present below the once-per-revolution (1P) frequency.

The low speed shaft torque is also alleviated for low frequencies (see Figure 8), but damage equivalent loads (DEL) can only be reduced by 5 % due to the dominant three-per-revolution (3P) frequency and the eigenfrequency of the drive train. Due to

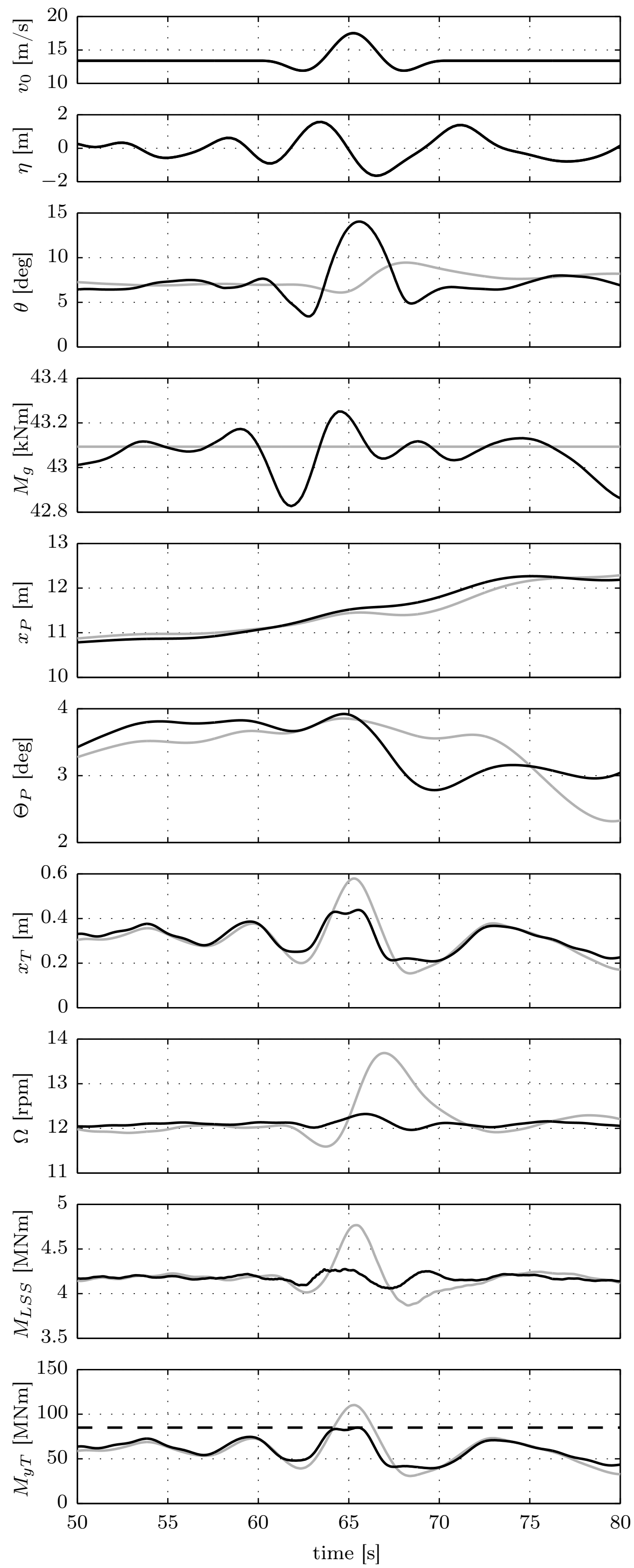

Figure 6: *Extreme load simulations: NMPC(black), BL(gray), constrain on tower fore-aft bending moment (dashed).*

Table 2: *Results of the normal operation simulations.*

	BC	NMPC	NMPC/BC
$\sigma(\Omega)$ [rpm]	0.854	0.089	10 %
$\sigma(P)$ [MW]	0.353	0.047	12 %
$\dot{\theta}$ [deg/s]	0.291	0.662	228 %
DEL(M_{yT}) [MNm]	177	176	99 %
DEL(M_{oop1}) [MNm]	11.3	10.6	94 %
DEL(M_{LSS}) [MNm]	2.20	2.09	95 %

the reduced gains of the baseline controller load reductions on the tower fore-aft bending moment seem to be hard to achieve. The spectrum can be lowered at the platfrom eigenfrequency (0.034 Hz) due to the weight on $\dot{\Theta}_P$, but no reduction can be achieved for the loads introduced by the waves $(0.05 - 0.3$ Hz) as well as for the loads close to the 3P frequency. The loads on the out-of-plane bending moment on blade 1 (M_{oop1}) is decreased by 6 %. But more simulations have to be done to give a realiable estimation of the load reductions.

There is a high increase in the pitch actuation, but it is hold below the values for the onshore turbine with the baseline controller and regular gains (up to 1 deg/s). Although a 3P notch filter is used for the full $\boldsymbol{x}$ vector transfered to the NMPC, the spectrum shows that the excitation is mainly in the frequency domain where no effect on rotor speed and tower for-aft bending moment can be observed. Therefore, the pitch action could be avoided by further filtering.

CONCLUSIONS AND OUTLOOK

In this work a nonlinear model predictive controller for a floating wind turbine is designed and compared to a baseline controller. A reduced nonlinear model is implemented in a NMPC algorithm to compute optimal input trajectories for collective pitch and the generator torque assuming perfect estimation of system states and perfect preview of the wind and waves disturbances. The controller is tested with a full aero-hydro-servo-elastic model disturbed by irregular waves and coherent hub height wind fields for extreme loads simulations and with a turbulent three-dimensional wind field for fatigue load simulations. Due to the capability to handle state constraints, the maximum load on tower can be lowered. Although the controller is able to reduce also fatigue loads on the shaft and blades, the main benefit is the reduction of the power and rotor speed standard deviation up to 90 %. Even if the NMPC controller is computationally more complex, the framework provides a “high performing” benchmark for development and comparison of less computationally-complex controllers.

In future work the controller will be tested for a full set of wind fields and waves. Furthermore, investigations concerning the influence on non-perfect state estimation and disturbance preview will be carried out as well as an extension for cyclic pitch control.

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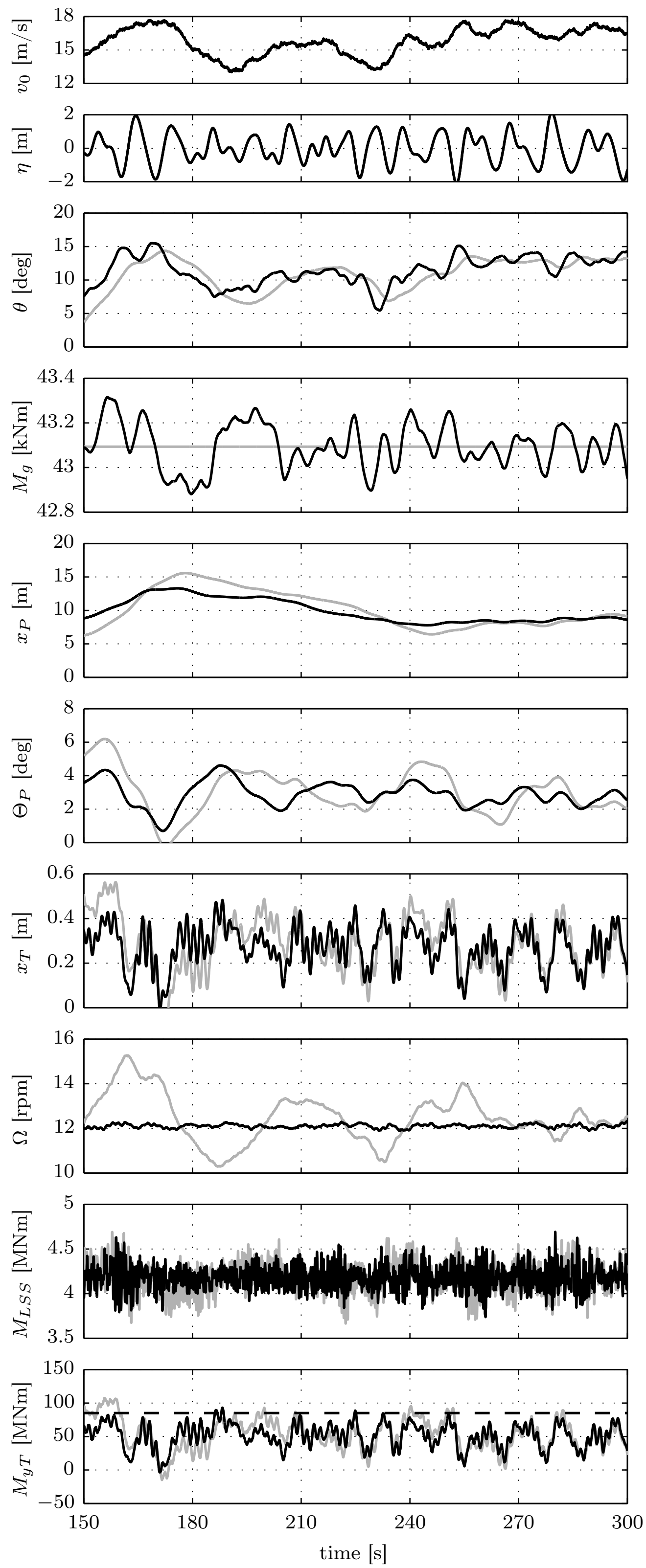

Figure 7: *Normal operation simulations: NMPC(black), BL(gray), constrain on tower fore-aft bending moment (dashed).*

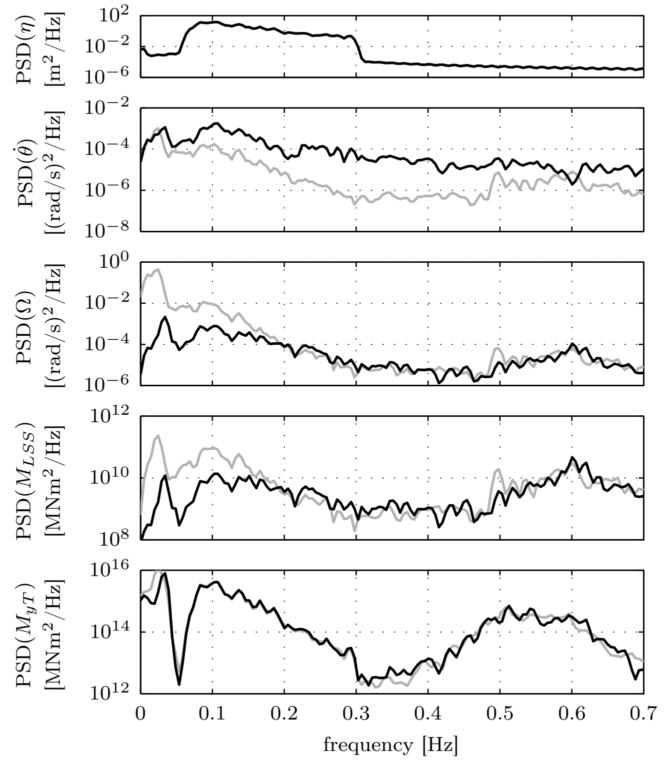

Figure 8: *Power Spectral Densities for the simulation from Figure 7, NMPC(black), BL(gray).*

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