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Published in:
American Control Conference (ACC), 2013

Publication date:
2013

Document Version
Publisher's PDF, also known as Version of record

2013 American Control Conference (ACC)
Washington, DC, USA, June 17-19, 2013

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Abstract— **Floating wind turbines are considered as a new and promising solution for reaching higher wind resources beyond the water depth restriction of monopile wind turbines. But on a floating structure, the wave–induced loads significantly increase the oscillations of the structure. Furthermore, using a controller designed for an onshore wind turbine yields instability in the fore–aft rotation. In this paper, we propose a general framework, where a reference model models the desired closed–loop behavior of the system. Model predictive control combined with a state estimator finds the optimal rotor blade pitch such that the state trajectories of the controlled system tracks the reference trajectories. The framework is demonstrated with a reference model of the desired closed–loop system undisturbed by the incident waves. This allows the wave-induced motion of the platform to be damped significantly compared to a baseline floating wind turbine controller at the cost of more pitch action.**

I. Introduction

In the demand for cheaper energy, the development in wind energy has gone from onshore to bottom–fixed wind turbines in shallow water where wind speeds are stronger and more steady. Previously, the bottom–fixed wind turbine has been installed in water depths of up to 50 meters. However, a new and promising development in wind energy reaches deep water locations of even higher wind speeds, based on the concept of a floating wind turbine (FWT). In Fig. 1 a sketch of a floating wind turbine is shown. The principle components, are a platform (yellow), the tower, the nacelle and the blades.

A wind turbine installation has one simple objective: to keep the lifetime cost of energy as low as possible. This involves a trade-off between power production and turbine lifetime.

The FWT is different from the onshore wind turbine, in the sense of structural degrees of freedom (DOF's) and the presences of waves. The response of a FWT is highly affected by the relatively slow hydrodynamics, causing a low natural frequency of the fore–aft rotation of the FWT. Although conventional onshore control is designed such that it does not excite the tower oscillations, applying the conventional onshore control strategies to FWT's has been shown to impose negative damped oscillations on the fore–aft rotation of the FWT.

To resolve this, in [1], a tower damping control strategy was introduced using a wind estimator showing reduced tower oscillations at the cost of reduced power output. In [2] a detuned gain scheduled proportional integrating controller was applied. A Linear quadratic control was applied in [3], [4], [5] where the two latter included wind and wave estimation combined in a full range control strategy. In [6] a disturbance accommodating control was applied to reduce the wind disturbance. In [7] a strategy for reducing the impact of waves was presented.

Model Predictive Control (MPC) is an attractive control method because of its capability to deal with constraints and to deal with multi-variable systems [8]. MPC solves an optimal control problem over a finite horizon repeatedly. Given the current state of the system, an optimal control problem over a finite horizon is solved at each time step. The optimal input sequence is found and only the first element of the sequence is applied to the system. At the next time step, a new optimal control problem is solved based on the new measurements from the system and the same procedure is repeated [9]. Recently, MPC is used with promising simulation results for control of non-floating wind turbines, see [10], [11], [12]. In [13], model predictive control is uses with the information about the future wind and a nonlinear model of the structural damages produced by repetitive loads to reduce the structural load and fatigue. In [14], the authors have used the wind prediction information obtained from a LIDAR system in a nonlinear model predictive controller to reduce fatigue loads on the tower and blades.

This paper presents a framework for specifying the desired closed-loop behaviour of the controlled system based on a control strategy including a reference model. Using model-based predictive control (MPC) the FWT is controlled to adapt to the behavior of a reference model. As an example, a FWT exposed to the disturbance of the waves is control using MPC with a reference model which models the behavior of the FWT in still water without the disturbance of the waves. This allows us to reduce the wave induced platform motions and loads on, e.g., the mooring system. The controller structure, allows other reference models, and as such is generally applicable to shaping the desired structural behavior.

This paper consist of a principle model presented in Section II-A. In Section II-B, stochastic models of wind and waves are presented. In Section II-D, a strategy for reference model-based predictive control is presented. In Section II-E, an extended Kalman filter (EKF) is used to estimate the unmeasured states and system matrices. In Section II-F, a closed–loop reference model is presented. In Sections IV and V, the results are presented and discussed. In Section VI, the contributions are concluded.

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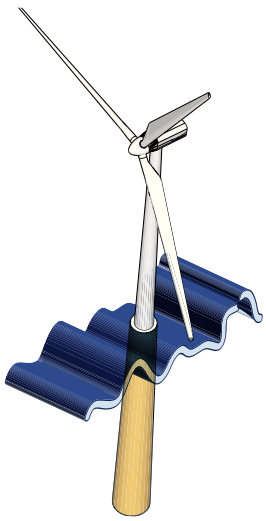

Fig. 1. Sketch of a ballast stabilized floating wind turbine.

II. Methods

A. Principle Model of Floating Wind Turbine

The dynamics of a floating wind turbine depends on the structural-, aero- and hydrodynamics as described in [4]. The hydrodynamics is a function of the wave frequency and surface smoothness of the structure. The aerodynamics is a function of wind speed and the efficiency of the rotor. The wind speed is obviously uncontrollable, however, the efficiency of the rotor can be controlled by altering the blade pitch angle and/or the rotor speed.

First, the aerodynamic impact on the FWT is investigated. Let us assume, a wind turbine can be modeled as a second order dynamical system by:

$$I\ddot{q} + C\dot{q} + Kq = F_{\text{wind}} + F_{\text{waves}}, \tag{1}$$

where $\dot{q} = [\ \dot{x}_p \quad \dot{\theta}_p \quad \Omega\ ]^T$ and where $\dot{x}_p$ is the platform translational velocity in fore–aft, $\dot{\theta}_p$ is the platform rotational velocity in fore–aft, and Ω is the rotor speed. Structural dynamics including the added mass of displaced water and hydrodynamic damping are defined as follows; I is the inertia, C is the damping, and K is the stiffness. The external forces from wind and waves are F_{wind} and F_{waves}, respectively.

The external forces from the waves are modeled as $F_{\text{waves}} = [\ 0 \quad M_w \quad 0\ ]^T$, where M_w is the induced moment by the incident wave. The external forces from the wind are $F_{\text{wind}} = [\ F_t \quad h_t F_t \quad M_a\ ]^T$ where F_t is the aerodynamics thrust force induced by the wind, h_t is the distance from the hub to the center of buoyancy (COB), and M_a is the aerodynamics torque. The aerodynamic loads are modeled as

$$F_t = \frac{1}{2}\rho A v_r^2 C_t(\lambda, \beta) \tag{2}$$

$$M_a = \frac{1}{2\Omega}\rho A v_r^3 C_p(\lambda, \beta), \tag{3}$$

where ρ is the density of air, A is the area swept by the rotor, $C_t(\lambda, \beta)$ is the thrust coefficient of the rotor as a function of tip speed ratio $\lambda = \Omega R / v_r$, and β which is blade pitch angle. $C_p(\lambda, \beta)$ is the power coefficient. The wind speed seen by the rotor can be defined as $v_r = v - \dot{x}_p - h_t\dot{\theta}_p$, where v is the ambient wind speed.

B. Stochastic Wind and Wave Models

The wind speed is modeled as $v = v_m + v_t$ where v_t is the turbulent wind and v_m is a slowly varying mean wind speed as described in [15]. These are modeled as

$$\dot{v}_t = \frac{-\pi v_m}{2L} v_t + w_1 \tag{4}$$

$$\dot{v}_m = w_2 \tag{5}$$

where L is the turbulence length scale and $w_{1,2}$ are Gaussian white noise process, and $w_{1,2} \in W(V_v)$. The covariance of the Wiener process is modeled in [15] as

$$V_v = \begin{bmatrix} \pi v_m^3 t_i^2 / L & 0 \\ 0 & V_{v2} \end{bmatrix}, \tag{6}$$

where t_i is the turbulence intensity and V_{v2} is the covariance of the slow varying mean wind speed, v_m.

The wave induced loads can be presented as $M_w = X_i(a_{w1} + a_{w2})$ where X_i is a wave frequency dependent constant which transforms the wave height into wave induced load. a_{w1} is a wave frequency dependent wave height and a_{w2} is a slowly varying drift height. In [16], an empiric modified Pierson–Moskowitz spectrum is presented. The wave spectrum can be linearized at a given wind speed and wave frequency. Assuming the spectrum is constant, a linear stochastic model can be used to describe the combined wave height by

$$\dot{a}_w = a_{w1} \tag{7}$$

$$\dot{a}_{w1} = -w_0^2 a_w - 2\lambda_0\omega_0 a_{w1} + k_0 w_3 \tag{8}$$

$$\dot{a}_{w2} = w_4 \tag{9}$$

where w_0, λ_0 and k_0 are parameters of the linearized wave spectrum concerning the wave frequency, the damping factor, and the gain, and where a_w is an internal state and $w_{3,4} \in W(V_a)$. The covariance of the Wiener process is modeled as

$$V_a = \begin{bmatrix} V_{a1} & 0 \\ 0 & V_{a2} \end{bmatrix}, \tag{10}$$

where V_{a1} is the covariance of the frequency dependent wave height, a_{w1}, and V_{a2} is the covariance of the slow varying drift height, a_{w2}.

C. Reference Model–Based Predictive Control

In the search to reduce the structural oscillation induced by the incident waves, we suggest a control strategy which will counteract the wave loads using blade pitch. The blade pitch is controlled using a model predictive controller which as an example is based on a reference model of the closed–loop system without disturbance from incident waves. The reference model produces the state trajectory of the controlled undisturbed system as a reference for the MPC. Using the blade pitch, the MPC will counteract the disturbance from

the waves and will try to track the closed–loop trajectory of the undisturbed reference model.

MPC is optimal for a finite horizon, however, using a reference model of the closed–loop system does not guarantee optimal performance of the process. It only guarantees optimal performance in the sense of tracking the state trajectories of the desired closed–loop system. The controller included in the reference model is a classical PI controller, which is not an optimal design.

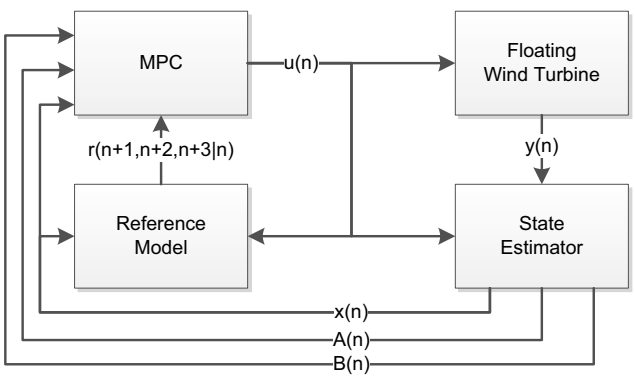

Fig. 2. Control strategy comprising of a state estimator, a reference model and an MPC controller.

In figure 2 the general control framework is presented as a block diagram. To capture the nonlinear behavior of the systems at different operating points, at each sample time the nonlinear model is linearized at the current state. Therefore, a state estimator is implemented, since the MPC requires knowledge of the current states and the open–loop system matrices of the process. Using a reference model–based predictive control also requires a closed–loop model of the desired response of the system. A closed–loop reference model is implemented which estimates the closed–loop response three samples ahead.

The overall control strategy is as follows. The state estimator estimates the current state of the system. Then, the nonlinear model of the FWT is linearized at the current operating point and the open-loop matrices of the system are calculated. These matrices are assumed to be constant in the prediction horizon. Then, the closed-loop reference model generate state trajectories of the undisturbed system as a reference for the states of the disturbed system. Given these references, the MPC will control the system by manipulating the blade pitch such that the states of the system tracks the trajectories produced by the reference model as close as possible.

In the following, the state estimator, the reference model, and the MPC will be described in details.

D. Model Predictive Controller

The goal of the model predictive controller in the example discussed in this paper is to reduce the effect of incident waves such that the controlled system has the closest possible response to that of the undisturbed system without violation of constraints. Assume that the general model of the disturbed open–loop system is given as:

$$\begin{aligned} x(k+1) &= A_w x(k) + B_w u(k), \\ y(k) &= C_w x(k). \end{aligned} \tag{11}$$

where the disturbance is included in the state vector and the open–loop model of the undisturbed plant is given by:

$$\begin{aligned} x_r(k+1) &= A_r x_r(k) + B_r u_c(k), \\ y_r(k) &= C_r x_r(k), \end{aligned} \tag{12}$$

where the pre-designed controller for the undisturbed plant is described by:

$$\begin{aligned} x_c(k+1) &= A_c x_c(k) + B_c y_r(k) + E_c r(k), \\ u_c(k) &= C_c x_c(k) + D_c y_r(k) + F_c r(k), \end{aligned} \tag{13}$$

where r is an internal reference signal. Here, the controller is a classical PI which is explained in subsection II-F. We assume that the states and input must be bounded in a given compact polyhedral set given respectively by $\mathcal{X}$ and $\mathcal{U}$. Then, the model predictive controller solves the following optimization problem at each step:

$$\min_{\{u(k),\ldots,u(k+T-1)\}} \Sigma_{k=k_0}^{T} \|x(k) - x_r(k)\|_Q^2 + \|u(k)\|_R^2 \tag{14}$$

$$s.t. \begin{cases} x(k_0) = x_0 \\ x_r(k_0) = x_{r0} \\ x(k+1) = A_w x(k) + B_w u(k), \\ y(k) = C_w x(k), \\ x_r(k+1) = A_r x_r(k) + B_r u_c(k), \\ y_r(k) = C_r x_r(k), \\ x_c(k+1) = A_c x_c(k) + B_c y_r(k) + E_c r(k), \\ u_c(k) = C_c x_c(k) + D_c y_r(k) + F_c r(k), \\ x(k) \in \mathcal{X}, \\ u(k) \in \mathcal{U}, \\ k = k_0, \ldots k_0 + T, \end{cases} \tag{15}$$

and finds the input sequence $\{u(k), \ldots, u(k+T-1)\}$. The first element of the sequence i.e $u(k)$ is applied to the system and the whole procedure is repeated in the next iteration. In the above optimization problem the initial state of the system as well as the initial states of the reference model are updated at each iteration using a state estimator in form of an EKF. Also, to update the matrices of the model with respect to the current states, the nonlinear system is linearized at each iteration around the current state. The system is considered as time invariant during the prediction horizon which means that these matrices are the same for the whole prediction horizon.

E. State Estimation

Since the states related to the wind and waves are not always available on a wind turbine, stochastic models of wind and waves are used to estimate these states.

The system outputs which are assumed to be measured are $y = [x_p \ \theta_p \ \Omega]^T$, where x_p is the platform translational velocity in fore–aft, θ_p is the platform rotational velocity in fore–aft, and Ω is the rotor speed.

Based on the available measurements, an EKF is implemented to estimate the unmeasured states as described in [15]. The deterministic model in Eq. (1–3) and the stochastic model in Eq. (4–9) are combined in the estimator.

The output of the state estimator is a state vector and the system matrices of the linearized open–loop system at the current state.

F. Reference Model

The reference model resembles the dynamics of the closed–loop system of a floating wind turbine described in Sec. II-A augmented with a baseline controller designed for a floating wind turbine as described in [17], [18].

The baseline controller consists of a blade pitch controller combined with constant generator torque. The pitch controller is a gain scheduled PI controller modeled by

$$\beta = \frac{1}{1 + \frac{\beta}{\beta_k}} PI(\omega_{\text{ref}} - \omega), \tag{16}$$

where β is the blade pitch angle, β_k is a constant, and ω_{ref} is the generator speed reference. The constant generator torque is implemented by

$$M_g = P_{\text{rated}}/\omega_{\text{rated}}, \tag{17}$$

where P_{rated} is the rated power and ω_{rated} is rated generator speed.

The stochastic wave model is not included in the closed–loop reference model since this is an undesired disturbance that we wish to compensate for. Thus, for the closed–loop system, the wave model in Eq. (7–9) is modeled as

$$\dot{a}_w = 0 \tag{18}$$
$$\dot{a}_{w1} = 0 \tag{19}$$
$$\dot{a}_{w2} = 0, \tag{20}$$

where the initial conditions are $a_w = a_{w1} = a_{w2} = 0$.

III. Experimental Setup

A. Simulation Environment

The wind is simulated with a mean wind speed of 18 m/s, an air density of 1.225 kg/m^3, and a turbulence intensity of 15%.

The waves are simulated as irregular waves with a JONSWAP/Pierson–Moskowitz spectrum [19]. The significant wave height of the incident waves is 6.9 meters with a wave frequency of 7.8 seconds. The environmental conditions are simulated in waters, with a depth of 320 meters and a water density of 1025 kg/m^3. The waves are aligned with the direction of the wind.

B. Model-Based Predictive Control

The parameters of the optimization problem of the MPC are chosen as follows $R = (20\text{deg})^{-2}$ and $\mathbf{Q} = \text{diag}\left([\mathbf{0_{1\times3}} \ \mathbf{Q_s} \ \mathbf{0_{1\times2}}]\right)$. The weighting of the structural states, $\mathbf{Q_s}$, are based on Brysons's rule were the initial guesses are 20% of the steady state operating points while using trail and error with respect to the integrated rotor speed. Thus we choose $\mathbf{Q_s} = \left[(0.2\bar{x}_p)^{-2} \ (0.2\bar{\theta}_p)^{-2} \ (0.07\Omega)^{-2} \ \mathbf{0_{1\times2}} \ (0.2\Omega)^{-2}\right]$, where the steady state operation points are $\bar{x}_p = 12.1$m, $\bar{\theta}_p = 2.55$deg and $\bar{\Omega} = 12.1$RPM.

C. Software

The wind turbine is a three bladed upwind 5MW reference wind turbine specified by the NREL in [18], and implemented in the wind turbine simulation tool FAST, which is well recognized in the OC3 code benchmark, [20]. The implementation of the wind turbine installation consists of a 5 MW wind turbine mounted on a ballast-stabilized buoy, to resemble an upscaled version of the 2.3 MW Hywind wind turbine. The floating wind turbine has a rotor radius of 63 meters, a tower height of 90 meters, six degrees of platform freedom, and flexible tower, blades and drivetrain.

The simulations were performed in Simulink Matlab v7.9.0 (R2009b) linked with FAST v7.00.00a-bjj and AeroDyn v13.00.00a-bjj compiled for the OC3 Hywind running Windows 7 -32bit.

IV. Results

The results shows the response of the FWT when applying the baseline controller and the MPC controller. In all cases the wind turbine is released from an upright position and forced backward by the wind and waves.

The controlled systems are simulated with incident waves for 600 seconds divided in to 0–300 seconds and 300-600 seconds in figure 3 and 4, respectively. Furthermore the baseline controller is simulated without incident waves which demonstrate the optimal reference for the MPC controller.

The FWT is constrained by three anchors. A mooring system connects the anchors to three fairleads on the FWT. In figure 5, the tension on the three fairleads are presented. The fairleads are located on the platform with 120 degrees in between, where fairlead 1 is located at 180 degrees in relation to the incoming wind and waves.

In figure 6 a statistical analysis is presented, where the performance of the two controllers are compared. In relation to the results in figure 3–5, the analysis is performed on the time interval 100–600 seconds to neglect the initial process behavior.

V. Discussion

When comparing the time–series performances in figure 3 and 4, the similarities in performances are noticeable. The similar behavior is caused by the almost similar objectives, except for the desire to reduce wave disturbance.

In figure 4, it is clear that the blade pitch of the baseline controller only correlates to the mean of the wind speed,

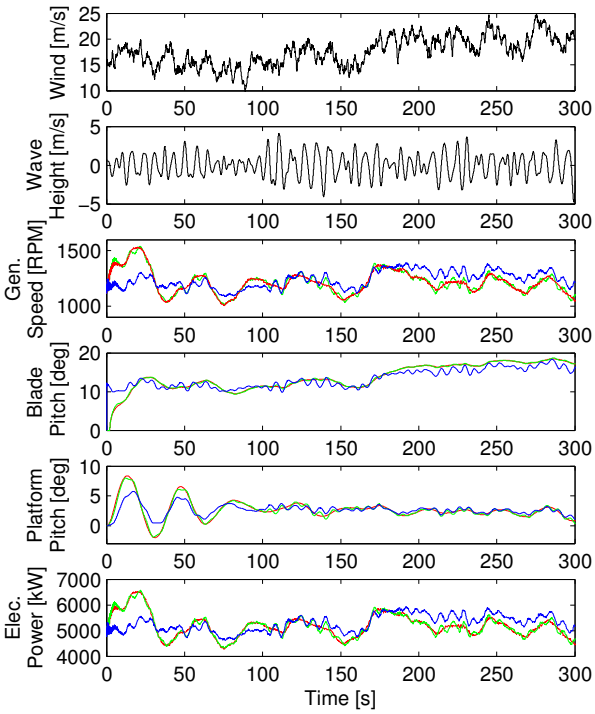

Fig. 3. Showing 0–300 seconds of the 600 seconds comparison between the baseline controller without waves (red), the baseline controller with waves (green) and the MPC controller with waves (blue).

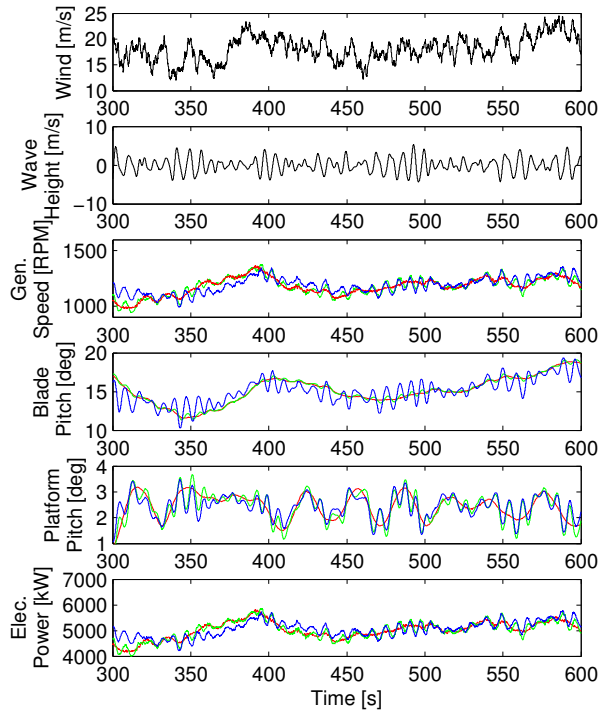

Fig. 4. Showing 300–600 seconds of the 600 seconds comparison between the baseline controller without waves (red), the baseline controller with waves (green) and the MPC controller with waves (blue).

while the blade pitch of the MPC controller correlates with both the mean wind speed and wave height. As expected, this causes an increase in blade pitch activity by the MPC controller. However, the benefit is observed as a reduction in platform pitch.

A reduction in platform pitch reduces the variations in tension on the mooring system. In figure 5, the tension of the three fairleads are presented. The figure shows a general reduction in load oscillations on the fairleads, where the tension of fairlead 1 is aligned with the direction of the wind and waves. This explains the reduced mean load on fairlead 1. The fairleads are connected to the anchors by the mooring lines.

In figure 6, the time–series are analyzed with respect to the standard deviation (std) and the distance travel by the blade pitch (abs) defines as $\int |\dot{\beta}| dt$ and damage equivalent load (DEL). The figure shows that the MPC performs better in the power, platform pitch and fairlead tensions. As expected, the blade pitch activity has increased which explains the increase in DEL of the tower in fore–aft. In other words, the controller uses not only the blade pitch and rotor thrust to reduce the wave disturbance, but also the tower experiences higher levels of loads in the combined effort to reduce the wave disturbance.

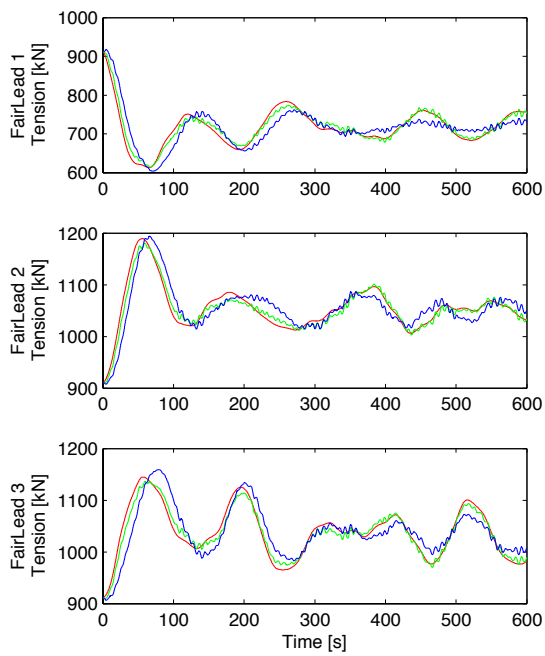

Fig. 5. Comparison of loads on the three fairleads between the baseline controller without waves (red), the baseline controller with waves (green) and the MPC controller with waves (blue).

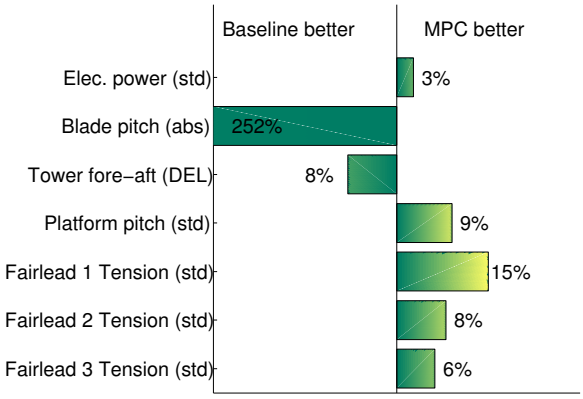

Fig. 6. Statistical analysis of essential performance indexes, where (std) is standard deviation, (abs) is the total traveled distance, and (DEL) is damage equivalent loads.

VI. Conclusion

A framework for reducing the wave disturbances in a FWT based on MPC combined with a reference model and a state estimator has been presented. The presented state estimator is based on a principle model of a FWT, including stochastic models for wind and waves. The reference model represents a closed–loop model of the FWT, including a baseline controller, discarding the wave disturbances. The MPC controller finds the optimal control input such that the state trajectory of the FWT tracks the reference trajectory generated by the reference model. As a result, the behavior of the FWT would be close to the behavior of the system response in still water without considering the wave disturbances.

As expected, an increase in the blade pitch activity is necessary to reduce the wave disturbance. Besides a slight power improvement, the results shows that oscillations on the platform pitch are effectively reduced, which result in reduced oscillations of the loadings on the fair leads. A disadvantage in the application example is the increase in tower fore-aft deflection.

The generality of the proposed framework with a reference model allow such concerns to be addressed by modifying the reference model. This will of course have a cost back on the blade pitch activity or the loadings on the fairleads and as such clearly demonstrate the trade-off between pitch activity, tower deflection and load oscillations.

VII. Acknowledgment

This work has been funded by Norwegian Centre for Offshore Wind Energy (NORCOWE) under grant 193821/S60 from Research Council of Norway (RCN). NORCOWE is a consortium with partners from industry and science, hosted by Christian Michelsen Research.

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