Reducing Blade Fatigue and Damping Platform Motions of Floating Wind Turbines Using Model Predictive Control

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ABSTRACT: With the recent trend in wind industry to invade deep water, floating platforms are becoming an active area of research and development. The floating platform adds extra degrees of freedom (DOFs) to the turbine structure, these added DOFs, if not taken into account actively or passively, can negatively affect the power production and turbine structural loading. The load comparison between the land-based and floating turbines shows an increase of up to seven times in floating turbines structural loading. Therefore, the development of new control systems for floating turbines become a necessity. One of the potential control approaches rely on the use of traditional control methods used by land-based turbines that employ the collective or individual blade pitch control. This paper presents a new method to control floating wind turbines in the above-rated region for reducing platform motion in addition to mitigating blade loads. The new method uses the model-based predictive control framework. The reduction of platform pitch motion, which is a significant problem for floating structures, is achieved by making the rated generator speed a function of the platform pitch velocity. The individual blade pitching is employed to accommodate the asymmetric aerodynamic loading over the rotor disk in order to reduce platform yaw motion and to mitigate blade loading. The conflict between the set objectives is solved by combining them into a single cost function that is minimized online at each time step to obtain the optimal individual blade pitching commands. Simulation results show a substantial reduction in platform motions at the cost of a minor increase in generator power error. Moreover, the blade flap-wise in addition to tower base fore-aft and side-side damage equivalent loads are also reduced.

KEY WORDS: Model predictive control; Individual blade pitching; Floating wind turbine.

1. INTRODUCTION

With the steady increase in wind power worldwide, offshore wind farms are most likely to be a sizable contributor of electricity production in some countries due to the high quality of offshore wind resources and their proximity to the big shore cities. To date, offshore wind turbines are limited to shallow water supported by the conventional fixed-bottom mono-pile structures [1]. For deeper water more than 60m these support structures are no longer economically feasible, and new types of turbine support are needed. Floating support platforms are one of the potential solutions. Several floating structures are studied, including barge, spar-buoy, and tension leg platforms [2], [3] (Figure 1). Recently, in June of 2009, the world’s first spar-bouy supported floating wind turbine was installed off the coast of Norway in 220m deep water [4].

The floating platform introduces six degrees of freedom (DOFs) to the system; These added DOFs, if not taken into account actively or passively, can negatively affect the power production and turbine structural loading. The load comparison between land-based and floating turbines shows dramatic increase in the loading of the floating structure, basically, in tower base fore-aft and side-side bending moments, blade flap-wise and edge-wise bending moments and drive-train torsional loading [5]. This overall increase in structural loading is related to the motion of the platform in the fore-aft direction (platform pitch motion) that induces the oscillatory wind inflow relative to the rotor, and excites the gyroscopic yaw moment in combination with the spinning inertia of the rotor. Therefore, the development of new wind turbine control systems that can reduce platform motions, while regulating power output and reducing structural loading become a necessity.

![Figure 1: Floating platforms concepts](image-url)

The control of floating wind turbines is relatively a new area of research. One of the first attempts in this direction was done by Nielsen et al., where they developed and tested an active
control strategy that takes into account the negative damping of the platform pitch motion introduced by the reduction of thrust force as the wind speed increases in the above-rated region (known also as region III, Figure 2). The study considered a spar-buoy platform (Figure 3). Simulations and experimental results on a scaled model provided satisfactory results in damping platform motion in the above-rated region [6].

Another study using the spar-buoy concept was done by Larsen and Hansen, where the baseline gain-scheduled proportional integral blade pitch (GSPI) controller in addition to proportional integral (PI) torque controller were designed to stabilize the floating system by limiting the blade pitching action such that it became slow compared to the tower motion. This approach showed improvements in blade and tower fatigue life, however, the output power was affected [2].

Several control strategies have been investigated by Jonkman in his attempts to increase the damping of the barge platform pitch motion [7]. For this purpose, he implemented the GSPI blade pitch controller along with a torque control with constant power algorithm to control a 5MW wind turbine mounted on a barge platform. Jonkman was successful in reducing barge platform pitch motion by detuning the GSPI gains. Moreover, he has found out that neither using a tower top feedback nor changing the control strategy to pitch to stall (instead of feather) were capable of reducing the pitch motion of the barge platform. However, one of Jonkman’s recommendations is to use the potentials of the multi-input multi-output (MIMO) state-space-based control systems, which are not yet extended to floating wind turbines.

Following Jonkman’s recommendation, Namik et al. designed a time-invariant linear quadratic regulator (LQR) that utilize the collective blade pitch angle [8]. The set objectives are regulating rotor speed and minimizing platform pitch motion. Testing results of this controller using the same 5MW wind turbine mounted on barge platform clearly presented an improved speed as well as platform pitch regulation when compared to the detuned baseline GSPI controller [7]. However, this controller had some limitations due the conflicting blade pitch commands issued to the collective blade pitching (CBP).

To overcome the limitations of the CBP, Namik and Stol implemented an individual blade pitching (IBP) periodic controller [9]. However, simulation results demonstrated that the periodic IBP controller destabilized some of the turbine degrees of freedom (DOFs). These DOFs (platform roll, drive-train, and first tower side-side bending mode) had to be included in the controller design in addition to the main controller objectives. Furthermore, Namik and Stol implemented a disturbance accommodating controller (DAC) to minimize the effects of wind disturbance over the turbine [9]. Although the DAC was found to be stable in the linear model around the linearization point, platform yaw is severely affected. Including this DOF into the controller design significantly improved performance by lowering the DAC gains and reducing platform yaw motion; Moreover, they found that the performance was heavily influenced by actuator saturation and turbine nonlinearities.

In more detailed studies, Namik and Stol have shown that the IBP controllers, applied on a 5MW floating barge wind turbine system can achieve significant reduction in platform pitch motion as the IBP creates asymmetric aerodynamic loads to restore platform pitch motion [10], [8], [11]. Their simulation results demonstrated a reduction in platform pitching motion by 30%, in tower fore-aft fatigue damage equivalent loads (DEL) by 20%, tower side-to-side fatigue DEL by 40% and the power variability be approximately 25%. The only drawback of this improved performance is the 10% increase in the blade root flap-wise bending moment fatigue load, however, this increase in blade root moment is - to some limit - expected given the physical mechanism used to control the platform motion by creating non-uniform thrust loads on the blades to generate a rotor tilt moment.

Meanwhile, Lackner tried to achieve the same objectives as Namik while reducing the blade loads [13]. For this purpose, he used two control loops, the variable power collective pitch control (VPPC) which uses the platform pitch velocity as a set point for generator speed, and the individual blade pitch control designed to reduce blade fatigue loading. Both control loops were implemented simultaneously in order to achieve the overall target objectives. Simulation results on a barge-mounted floating 5MW wind turbine compared to the detuned baseline GSPI controller showed that the suggested approach was able to reduce the tower fore-aft DEL by 11.7%, the root mean square (RMS) of the platform pitch angle by 15.4% and the RMS platform pitch rate by 15.7% on average, while this good performance was accompanied by an increase in RMS power error by 9.4% and generator speed error RMS by 4.5% on average. Moreover, the IBP control loop introduced a moderate reduction in the blade flap-wise DEL by only 1.2% on average. The main drawback of this approach is the tower side-to-side DEL that was originally reduced by 9.2% when the VPPC is used alone, this reduction is negated with the usage of the IBP controller. Based on that, Lackner came to the conclusion that the individual blade pitching is not that effective in reducing blade fatigue loading due to the overall blade loading which is approximately 60% larger in the floating platform compared to the land-based turbines [5].

On the other hand, the model predictive control (MPC) is an active research area for wind turbine control, as it provides a
systematic way to include future predictions or measurements (e.g. wind), constraints handling (e.g. blade pitch actuator limits) and achieving multi-objective tasks. One of the early implementations of MPC in wind turbine control is done by Kumar and Stol where different MPCs are designed and compared to the baseline GSPI controller tested on a land-based wind turbine [14]. The MPC has shown the ability of better regulation of rotor speed, and reduction of tower fore-aft and side-to-side fatigue loading, however, the improved performance came with an increased blade flap-wise DEL. Laks used the MPC to compensate wind disturbances measured in front of the turbine using LIDAR system [15]. Kumar used the MPC in order to compensate for the nonlinearities of the wind turbine model [16]. Other implementations of the MPC control could also be found in [17], [18], [19], where the different MPCs are tested on land-based turbines. One of the early attempts to employ the MPC to control floating wind turbines is presented by Chaaban and Fritzen [20], where the MPC for a floating 5MW wind turbine is implemented with the objective to stabilize platform pitching motion. The simulation results based on a two DOFs model has shown the possibility to reduce the pitching motion of the platform while keeping the generator speed at its rated value and respecting blade pitching actuators limits. This good performance came at the cost of increased tower base bending loads.

The focus of this work is to employ the model predictive framework for further investigation of the potentials and limitations of the usage of IBP in floating wind turbine control. The target objectives to achieve are: reducing the platform pitching motion while regulating rotor speed and reducing blade fatigue loading. The motivations to employ the MPC are on the first hand, to avoid conflict commands between two control loops that negates the good performance for each loop alone by combining all the targets in one cost function, and on the other hand, to employ better schema in handling pitching actuators limitation, which is expected to overcome the performance degradation due to actuators saturation.

The paper is organized as following: section 2 presents the linear turbine model, the model predictive controller structure in addition to the used simulation environment, while section 3 analysis the obtained simulation results and compare them to the reference baseline GSPI controller, finally section 4 states the final conclusion of this study.

2. MODELING, CONTROL AND SIMULATION

2.1. Turbine Model

The NREL offshore 5MW baseline wind turbine [21] is used for model development and simulation. This turbine is a fictitious 5MW machine with its properties based on a collection of existing wind turbines of similar rating since not all turbine properties are published by manufacturers. The turbine is mounted on the barge platform as shown in Figure 1. The barge is a rectangular platform designed to be a cost effective and easy to install platform and suitable for shallow water. It utilizes the buoyancy due to its large water-plane area to maintain stability. Since most of the platform is above the water, it’s very sensitive to incident waves. The main properties of this turbine and the barge platform are listed in Table 1. The used barge platform model is as implemented by Jonkman [5] and the full nonlinear wind turbine model is implemented in the aero-hydro-servo-elastic simulation code FAST [22]. However, the control and simulation are implemented in Matlab/Simulink.

A simple model of seven DOFs is used for controller design (referenced later as ‘7DOFs model’), this model includes: generator inertia, drive-train torsional mode, tower fore-aft and side-to-side first bending mode, and the platform rotational DOFs, namely: roll, pitch and yaw (Figure 3). This simple model is compared to the full DOFs model (21DOFs model) that is possible to obtain using FAST (all DOFs in FAST model are enabled except nacelle yaw, and rotor teeter DOFs). The frequency response of the generator speed and platform rotations to the collective blade pitch input for both models (see Figure 4) clearly shows that the 7DOFs linear model captures almost all the system dynamics in the lower frequency range (upto 1Hz) for the generator speed and the platform pitching motion, and to less accuracy for the roll and yaw motions. As the main task for the controller is to keep the generator speed at its rated value and to reduce platform pitching motion, and as blade pitching actuators are to operate in the lower frequency range, the 7DOFs model is found to be good enough for the controller design.

The above-rated region is the operating region considered
Table 1: Floating turbine properties [5]

<table>
<thead>
<tr>
<th>Turbine</th>
<th>Rated power</th>
<th>5MW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rotor type, blades</td>
<td>Upwind / 3 blades</td>
<td></td>
</tr>
<tr>
<td>Control</td>
<td>Variable Speed &amp; Variable Pitch</td>
<td></td>
</tr>
<tr>
<td>Rotor, hub diameter</td>
<td>126m/3m</td>
<td></td>
</tr>
<tr>
<td>Hub height</td>
<td>90m</td>
<td></td>
</tr>
<tr>
<td>Cut-in/cut-out wind speed</td>
<td>3(^{\frac{2}{3}}), 11.5(^{\frac{2}{3}}), 25(^{\frac{2}{3}})</td>
<td></td>
</tr>
<tr>
<td>Rated rotor speed</td>
<td>12.1rpm</td>
<td></td>
</tr>
<tr>
<td>Rated generator speed</td>
<td>1173.7rpm</td>
<td></td>
</tr>
<tr>
<td>Blade pitch rage</td>
<td>(-1\text{deg}, ..., +90\text{deg})</td>
<td></td>
</tr>
<tr>
<td>Max. blade pitch rate</td>
<td>(\pm 8.25\text{deg/s})</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Barge platform</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length</td>
</tr>
<tr>
<td>Width</td>
</tr>
<tr>
<td>Height</td>
</tr>
<tr>
<td>Draft</td>
</tr>
<tr>
<td>Water depth</td>
</tr>
<tr>
<td>Platform mass</td>
</tr>
</tbody>
</table>

due to the fact that platform pitch motion is excited in this region because of the negative damping introduced by the reduction of thrust force as the wind speed increases. As the control objective of the region II is to optimize power extraction by changing rotor speed at maximum aerodynamic performance of the rotor, this region is considered out of the scope of this study. Based on that, the 7DOFs linear model is obtained by FAST in the above rated region at operating wind speed \(w_{\text{wind}}^{\text{op}} = 18\text{m/s}\), and at the rated rotor speed \(\Omega_{\text{op}} = 12.1\text{rpm}\). FAST numerically linearizes the aeroelastic equations of motion by perturbing (represented by a \(\Delta\)) each of the system variables about their respective operating point (\(\ast_{\text{op}}\)) values. The linear model obtained from FAST has three inputs (the individual blade pitching commands), one disturbance input which is the hub height horizontal wind speed, and seven measured outputs which are: the generator speed, the platform roll, pitch and yaw angles, the flap-wise blades root moments. As the inputs to the linear model are given in the rotating frame of the rotor, they are transformed to the non-rotating frame of the tower using the multi-blade coordinate (MBC3) transformation [23]. The MBC3 transformation is also applied to the measured blade root moments in order to get these measurements into the non-rotating frame. The MBC3 transformation does not affect the states and disturbance vectors as they are already in the tower non-rotating frame. The final state space model is given as

\[
\begin{align*}
\Delta \dot{x} &= A \Delta x + B \Delta u_{\text{NR}} + B_d \Delta w \quad (1) \\
\Delta y &= C \Delta x + D \Delta u
\end{align*}
\]

where \(\Delta x\) is the perturbed state vector, \(\Delta u_{\text{NR}} = \begin{bmatrix} \Delta \theta_0 & \Delta \beta_0 & \Delta \beta_1 & \Delta \beta_2 & \Delta \beta_3 & \Delta \beta_4 & \Delta \beta_5 \end{bmatrix}^T\) is the perturbed input vector in the non-rotating frame (indicated by index \(\ast_{\text{NR}}\)) with collective \(\Delta \theta_0\), cosine \(\Delta \beta_0\) and sine \(\Delta \beta_1\), perturbed components, \(\Delta w\) is the perturbed wind disturbance input, the measured perturbed output vector is given as

\[
\Delta y = \begin{bmatrix} \Delta \Omega_g & \Delta \xi_r & \Delta \xi_p & \Delta \xi_y & \Delta M_0 & \Delta M_r & \Delta M_y \end{bmatrix}^T \quad (3)
\]

with \(\Delta \Omega_g\) is the perturbed generator speed, \(\Delta \xi_r, \Delta \xi_p, \Delta \xi_y\) are the perturbed platform roll, pitch and yaw angles respectively, \(\Delta M_0\) is the perturbed collective component that is useful for power generation, and \(\Delta M_r, \Delta M_y\) are the perturbed tilt and yaw moments that the blades exert on the hub of the rotor respectively. The system matrices \(A, B, B_d, C, D\) are of appropriate dimensions. The MBC3 transformation between the rotating coordinates \(q\) and the non-rotating coordinates \(\bar{q}_{\text{NR}}\) is given as

\[
q = T \bar{q}_{\text{NR}} \quad (4)
\]

and

\[
T = \begin{bmatrix} 1 & \cos \psi_1 & \sin \psi_1 \\ 1 & \cos \psi_2 & \sin \psi_2 \\ 1 & \cos \psi_3 & \sin \psi_3 \end{bmatrix} \quad (5)
\]

where \(\psi_1\) is the azimuth angle of the first blade, \(\psi_2 = \psi_1 + \frac{2\pi}{3}\) and \(\psi_3 = \psi_1 + \frac{4\pi}{3}\) are the azimuth angles of the second and third blades. The system model given in Equations (1, 2) should be transformed into discrete time domain before being used in the controller design, the used sampling time is set to \(T_s = 0.0125\text{sec.}\)
2.2. Turbine Control

2.2.1. MPC formulation

The model predictive control (MPC) is a framework in which the controller calculates the optimal control input trajectory to a system by minimizing a particular cost function $J$ over a finite period of time into the future (horizon) to calculate the optimum control moves. The optimization process might by subject to inputs and/or outputs constraints. The first control move is then applied to the system and the optimization problem is repeated at the next time step. The cost function can take several forms, one of the most used functions takes the quadratic form given in Equation (6). The optimization problem to be solved online is read as following

$$
\min_{\Delta U(k)} J(k) = \sum_{i=0}^{P-1} \left[ \frac{1}{Q} \| \tilde{y}(k+i) - y_{ref}(k+i) \|^2 + \| \Delta \hat{u}(k+i) \|^2_R \right]
$$

subject to

$$
\dot{x}(k+1) = A\hat{x}(k) + Bu(k) + B_d\psi(k) \tag{7}
$$

$$
y_{min} \leq \gamma(k) \leq y_{max} \tag{8}
$$

$$
u_{min} \leq u(k) \leq u_{max} \tag{9}
$$

where

$$
\Delta U(k) = \begin{bmatrix}
\Delta \hat{u}(k) \\
\vdots \\
\Delta \hat{u}(k+M-1|k)
\end{bmatrix} \tag{10}
$$

is the decision variable vector, $P$ is the prediction horizon, $M$ is the control horizon, $Q$, and $R$ are the weighting matrices on the outputs and inputs, $Q_f$ is the terminal weight and the associated terminal cost used to ensure closed loop stability, $y_{min}$, $y_{max}$, $u_{min}$, $u_{max}$ are the minimum and maximum output values, and $\Delta \hat{u}_{min}, \Delta \hat{u}_{max}$ are the minimum and maximum input values. The used norm in Equation (6) of a vector $\tilde{z}$ and a weighting matrix $W$ is given as

$$
\| \tilde{z} \|^2_W = \tilde{z}^T W^T W \tilde{z} \tag{11}
$$

and $\tilde{z}^T$ is the transpose of vector $\tilde{z}$. Equation (7) is the discrete time form of the system state Equation (1), and the matrices $A$, $B$, $B_d$ are the discrete form of the corresponding matrices in Equation (1). The last two lines in the optimization problem, Equations (8, 9), represent the constraints on outputs and inputs; another set of constraints might be also included. $\tilde{y}(k+i|k)$ and $\tilde{u}(k+i|k)$ are the estimated values of output and input vectors respectively for time step $k+i$ estimated at time step $k$. The estimation of the outputs, and consequently the states is done using Kalman filter [24].

2.2.2. Constraints

The pitching actuators pose two constraints on the controller, the first one is the pitching angle that should stay between lower and upper limits, and the second one is the rate of change of the pitching angle that should respect certain values, these constraints are given in continuous time in the rotating frame of the rotor as following

$$
u_{min} \leq u \leq u_{max} \tag{12}
$$

$$
u_{min} \leq u \leq u_{max} \tag{13}
$$

As the model uses perturbed inputs given in Equation (14) that have been transformed into the non-rotating coordinates of the tower, the given input constraints should be updated.

$$
u = \Delta u + u_{OP} \tag{14}
$$

Starting with the pitch angle constraints given in Equation (12), and using the transformation given in Equation (4), then combining the two inequalities into one, the new input constraint takes the following form

$$
E_1 \Delta \hat{u}_{NR} \leq G_1 \tag{15}
$$

where

$$
E_1 = \begin{bmatrix} T \end{bmatrix}
$$

$$
G_1 = \begin{bmatrix} u_{max} - u_{OP} \\ -u_{min} + u_{OP} \end{bmatrix} \tag{16}
$$

On the other hand, the constraints on the blade pitch rate are more difficult to handle as the transformation matrix $T$ is azimuth dependent, deriving Equation (4) will give

$$
\dot{\hat{u}} = T \hat{\nu}_{NR} + T \hat{\nu}_{NR} \tag{17}
$$

$$
\hat{T} = \psi T_1 \tag{18}
$$

$$
T_1 = \begin{bmatrix} 0 & -\sin \psi & \cos \psi \\ 0 & -\sin \psi & \cos \psi \\ 0 & -\sin \psi & \cos \psi \end{bmatrix} \tag{19}
$$

where $\psi$ is the derivative of the azimuth angle of the first blade with respect to time, in case of constant rotor speed, this derivative is equal to the rotor speed $\Omega$. Substituting Equations (19, 20) into Equation (18) and combining the two inequalities, the new constraint is given as

$$
E_2 \Delta \hat{u}_{NR} + E_1 \Delta \hat{u}_{NR} \leq G_2 \tag{20}
$$

where

$$
E_2 = \begin{bmatrix} \psi T_1 \end{bmatrix} \tag{21}
$$

$$
G_2 = \begin{bmatrix} u_{max} - \psi T_1 u_{OP} \\ -u_{min} + \psi T_1 u_{OP} \end{bmatrix} \tag{22}
$$

The constraints given in Equations (15, 21) should be transformed into discrete time before using them in the optimization problem. The implementation of the constraints assumes a constant rotor speed $\Omega$ which, as the simulation will demonstrate later, is not the case. However, this assumption did not affect the results as the constraints are not triggered during simulation.

2.2.3. Reference signals

The linear model obtained from FAST is a perturbed model at the considered operating point. This means that the input to the MPC should be the perturbed measurements given by

$$
\Delta \hat{\nu} = \hat{\nu} - \nu_{OP} \tag{23}
$$

where $\Delta \hat{\nu}$ is the measured error in the output, $\hat{\nu}$ is the estimated output, and $\nu_{OP}$ is the measured output.
where $\vec{z}_{OP}$ is the value of the measured outputs at the chosen operating point. As the main objective of the controller is to minimize platform motions and blade loading, using zero reference values for the perturbed platform motions and blade root moments would be appropriate. However, two methods could be considered for the reference value of the generator speed: The first method is to use zero reference, which means to force the controller to extensively use the individual blade pitching in order to build the asymmetric aerodynamic loading that can - to some limit - counteract the platform pitch and yaw moments. This will lead to a similar behavior to what is presented by Namik [8]. The second method is to use the scaled platform pitch rate as a reference by forcing the generator speed perturbation to be a function of the platform pitch rate; This means trading the reduction of platform pitch motion with the variation of generator speed so it increases when the turbine is pitching against the wind and decrease when the turbine is pitching with the wind. This change of control concept from constant generator speed at its rated value to a variable speed could be justified as the floating turbines are going to operate in floating farms where the overall power variability is more likely to be dependent on the condition of each turbine due to the spatial and temporal variations, rather than the variability of each turbine’s output. This method will give similar behavior to what is implemented by Lackner [13], with the advantage here of using one cost function instead of using two (or more) different control loops to achieve the set objectives. The second method is used in this study, leaving the first one for future work. The reference value for the perturbed generator speed is set as

$$\Delta \Omega_g = -b\dot{\xi}_p \tag{25}$$

where the scaling value $b$ is chosen to obtain about 10% error of the rated generator speed, that means about 10% error in the generator power as the generator torque is set to its rated value. This choice of $b$ will enable an easy comparison between the obtained results here and the results presented by Lackner [13].

### 3. RESULTS AND ANALYSIS

Two performance indices (PMs) are defined for better comparison between the controllers, these performance in-
The normalized performance indices are shown in Figure 7, where it is clear that the MPC shows a reduction in platform pitch RMS of 20% and its rate RMS of 16% at the cost of an increase of the generator power error of 11%. The reduction of platform pitch is combined by reduction of platform roll of 9%, yaw of 22%. This good performance in stabilizing platform motion is extended to reducing blade flap-wise DEL by 4% while the VPPC cause an increase by 1.4% (due to the usage of the IBP). Though, it is not fair to compare a simple control approach such as the VPPC (a single-input single-output (SISO) controller) to the advanced MPC that is a MIMO optimal controller, the obtained results reflects the benefits of using the MPC, as it can overcomes the conflicts between the set objectives and improve the performance.

The normalized performance indices are compared between the MPC and the variable power pitch control (VPPC) methods [13]. The performance of the MPC is clear in reducing blade flap-wise DEL by 4% while the VPPC cause an increase by 1.4% (due to the usage of the IBP). Though, it is not fair to compare a simple control approach such as the VPPC (a single-input single-output (SISO) controller) to the advanced MPC that is a MIMO optimal controller, the obtained results reflects the benefits of using the MPC, as it can overcomes the conflicts between the set objectives and improve the performance.

Time series results are shown in Figure 9, these plots illustrate the used wind and wave conditions, the performance of the pitching angle of the first blade, the reduction in generator power variation (generator torque is constant), the platform pitch response, and loading moments of the tower base fore-aft and side-side in addition to first blade flap-wise direction.

4. CONCLUSION

The performance of the floating wind turbines is highly affected by the platform motions, making the task of stabilizing platform motions a keystone to improve their performance. Addressing this problem within the model predictive control framework shows promising results. An improved performance is possible to obtain using an MPC with the objectives to reduce platform motion, tower base loading and blades loading while forcing the generator speed to follow the scaled platform pitch rate. Simulation results show a decrease in platform motion RMS, tower base DEL at the cost of minor increase in generator power error RMS. Moreover, employing the MPC enabled the IBP to achieve more reduction in blade flap-wise DEL and avoid the conflict between the different objectives.
REFERENCES


