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Observer based pitch control for load mitigation and power regulation of floating offshore wind turbines

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Abstract. Most commercial wind turbines use proportional-integral (PI) collective blade-pitch control to regulate rotor speed in the above-rated wind speed regime. A significant drawback of this type of controller is that it assumes that the blades have identical structural properties and are subject to similar aerodynamic loads, which is seldom the case. Also, these controllers are designed to regulate the rotor speed and are not designed for structural vibration/load reduction. However, it is well known that blade pitch control can reduce structural loads on wind turbines. This opens up the possibility of designing controllers that use existing actuators and sensors like the blade pitch actuators to reduce structural loads/vibrations while maintaining the required rotor speed. Recent studies have investigated individual blade pitch control (IPC) to address these shortcomings. However, the vast majority of studies published in the literature depend on the availability of state measurement. Although sensors are commonly placed on all wind turbines, and some information is readily available, the measurement required by the typical state-feedback controllers is usually not available. Displacements and velocities of the blade, the tower and the floating platform are difficult to measure. This paper develops an observer-based individual blade pitch controller for load mitigation and power regulation of floating offshore wind turbines. We propose to use a Kalman filter to estimate the state from the accelerometer and strain gauge measurement for use in the state-feedback controller. The state-feedback controller was proposed previously by the authors that showed excellent performance. This paper extends the capability of the state-feedback controller by designing an observer (Kalman filter) to estimate the state from limited measurements. The proposed observer based controller is compared against a baseline proportional integral collective blade pitch controller and full state-feedback controllers to evaluate its performance. Numerical results show that the proposed output feedback controller offers performance improvements over the baseline controller, similar to the full state-feedback controller.

1. Introduction

The future of wind energy lies offshore for several reasons. The wind speeds available offshore are higher than onshore wind speeds with lower levels of turbulence. This increases the power potential of offshore turbines and also leads to reduced fatigue loads on the structures. Floating Offshore Wind Turbines (FOWTs) have been proposed in recent years for deep water deployment where the installation of traditional fixed bottom turbines would be impossible. This opens up vast areas of the marine environment for offshore wind development. However, there remain significant technical challenges to be overcome to make floating offshore wind a commercially attractive prospect. In general the structural characteristics of a FOWT are much more dynamic than an onshore turbine or a traditional fixed base offshore wind turbine. Due to this fact, novel structures and controllers must be developed specifically for FOWTs. The stability of the FOWTs (pitching and rolling of the platform) and reduction of aerodynamic loads on FOWTs is now the topic of considerable research. Much work focuses on the design of new pitch and torque controllers.

Bossanyi [1, 2] proposed the concept of reducing aerodynamic loads through individual blade pitch control (IPC). The industry accepted these advanced control algorithms, and modern wind turbines are now actively pitched to reduce mechanical loads. Field experiments were further conducted by Bossanyi et al.[3] to validate the previously proposed IPCs.

Mughal and Guojie [4] presented a discussion on various pitch control strategies from primary PID (proportional-derivative-integral) controllers to complex multivariable controllers like H_∞, neural network, adaptive control. Namik and Stol [5, 6] proposed the most prominent IPCs for floating offshore wind turbines based on a State Feeback Controller (SFC) and a Disturbance Accommodating Controller (DAC). In [7] the authors demonstrated the performance of the above two controllers on a spar-buoy floating wind turbine. The authors showed that while both controllers can improve power regulation, the DAC has a detrimental effect on the platform motion. An advanced wavelet IPC was proposed by Sarkar et al. [8] for reducing aerodynamic loads on the floating wind turbine.

Model Predictive Control of wind turbines using LIDAR measurements providing information about wind at various distances in front of the wind turbine has also been studied in recent literature [9, 10, 11]. A nonlinear model predictive control for floating offshore wind turbines was investigated in [12, 13].

It can be noted here that, common to all the IPCs reviewed above, the controller typically assumes that information about the state is available in the form of measurements. However, this is seldom the case. Typically, displacements and velocities are difficult to measure. This paper proposes using a Kalman filter to estimate the state using strain gauges and accelerometer measurements that are much simpler and readily available. Researchers have used Kalman filters for various purposes like wind speed estimation [14] fault detection in blade pitch systems [15], estimating fatigue stress at critical locations using acceleration and thrust force measurements [16]. A modified application of the Kalman filter is presented here to tackle the fact that the plant (the FOWT) is subjected to non-zero mean coloured noise. Unlike traditional Kalman filters, the plant input is estimated from measurements rather than being known inputs. This enables one to tackle the fact that the plant is primarily excited by unknown non-zero mean coloured noise.

2. PROPOSED OBSERVER BASED CONTROLLER

A nonlinear aeroelastic 22-DOF model of the FOWT [17] has been used in this study to simulate its dynamic behaviour subjected to a stochastic wind-wave loading environment and evaluate the performance of the proposed controller. For brevity, details of the 22 DOF system are not presented in this paper. The reader will find more details in [18].

The controller strategy proposed in this paper is based on a reduced degree of freedom 6-DOF model. It consists of a continuous time Kalman filter coupled to a state-feedback controller proposed previously by the authors in [19]. This paper extends the capabilities of the previously proposed controller by coupling it to a Kalman filter to estimate the state from measurements. In the following subsections, first, the controller is summarized, then the proposed Kalman filter is presented.

2.1. Low authority Linear Quadratic controller

As shown in [19] the control input of the individual blade pitch angles are obtained as

$$\mathbf{\Theta} = \theta + \mathbf{\Theta}_l \tag{1}$$

where $\theta \in \Re$ is the collective pitch angle obtained from the integral controller and $\mathbf{\Theta}_l \in \Re^{3\times1}$ is the individual pitch angles obtained from a low authority LQ (Linear Quadratic) controller. The $\mathbf{\Theta}_l$ is obtained from a low authority steady-state LQ controller as

$$\mathbf{\Theta}_l = -\mathbf{R}^{-1}\mathbf{B}(\theta)^T\mathbf{P}\mathbf{x}(t) = -\mathbf{K}(\theta)\mathbf{x}(t) \tag{2}$$

Where, $\mathbf{P}$ is the solution of the algebraic Riccati equation associated with the reduced degree of freedom system, $\mathbf{B}(\theta)$ is the control input matrix, R is the input weight matrix and $\mathbf{K}(\theta)$ is known as the LQR gain. In the above equation the state of the reduced DOF system given as

$$\begin{aligned}\mathbf{q} = \{q_P \; q_{TFA1} \; q_{B1F1} \; q_{B2F1} \; q_{B3F1} \; q_\varepsilon\} \\ \mathbf{x} = [\mathbf{q} \quad \dot{\mathbf{q}}]^T\end{aligned} \tag{3}$$

Where the subscripts, $_P$ denotes the platform pitching mode, $_{TFA1}$ denotes tower first fore-aft bending mode, and $_{BiF1}$ denotes the first flapwise bending mode of the i^{th} blade. The LQ controller is combined with an integral action as shown in Figure 1. The integral controller has been obtained from [20]. For brevity, the derivation of the controller has been omitted from this paper, and the reader is referred to [19].

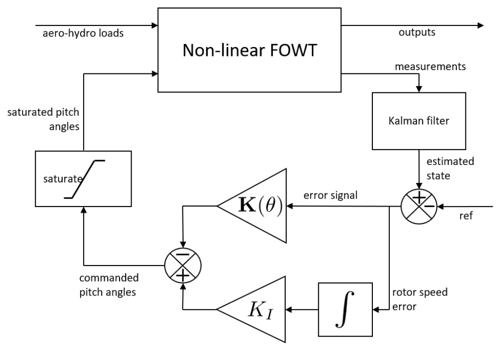

Figure 1. Controller schematic

2.2. Continuous time Kalman filter

It can be observed from equation (2), the LQ controller requires the complete state of the reduced DOF system to estimate the control input. However, measuring the velocities and displacements of the blades, the tower and the platform are typically more complicated and not readily available. Therefore, in this paper, a continuous-time Kalman filter is designed to estimate the system's state from accelerometer and strain gauge measurements. Three strain gauges are assumed to be located at the root of the three blades to measure the flapwise bending strain. Moreover, three accelerometers are used to measure the accelerations at the tip of the three blades.

The rotor speed is commonly an available measurement, hence, the speed error DOF in equation 3 is removed from the plant model used to develop the Kalman filter. Therefore, a 5-DOF model of the FOWT is used as the plant. The linearized 5DOF system can be written as

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{C}\dot{\mathbf{x}} + \mathbf{K}\mathbf{x} = \mathbf{f} \tag{4}$$

An approximation of the mass, damping and stiffness matrices are obtained from a linearization analysis. The force vector is obtained as

$$\mathbf{f} = \begin{cases} \int_0^{L_b} p_x^1(r)\phi(r)\mathrm{d}r \\ \int_0^{L_b} p_x^2(r)\phi(r)\mathrm{d}r \\ \int_0^{L_b} p_x^2(r)\phi(r)\mathrm{d}r \\ \sum_{i=1}^3 \int_0^{L_b} p_x^i(r)\mathrm{d}r \\ H_{hub} \sum_{i=1}^3 \int_0^{L_b} p_x^i(r)\mathrm{d}r \end{cases} \tag{5}$$

Where, $p_x^i(r)$ is the distributed flapwise force on the i^{th} blade, L_b is the length of the blade, $\phi(r)$ is the fundamental mode shape of the blade and H_{hub} is the height height of the turbine from the mean sea level (MSL). The above linearized plant system can be written in state-space form as

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{Ax} + \mathbf{Bu} + \mathbf{Gw} \\ \mathbf{y} &= \mathbf{Cx} + \mathbf{Du} + \mathbf{v} \end{aligned} \tag{6}$$

In conventional Kalman filter design, the control input vector $\mathbf{u} = \mathbf{f}$ is the known input to the plant. For the FOWT, the input to the system is the aerodynamic and hydrodynamic loads. These forces are generally unknown, have non-zero mean and are coloured in nature. In this paper, we propose that the inputs (i.e., only the aerodynamic forces) are estimated from the strain measurements in the case of unknown system inputs. The moments at the blade roots are estimated from the strain measurements as

$$M = \frac{\epsilon I}{y} \tag{7}$$

The moment on the blades due to the distributed aerodynamic loads can be approximated by a point load as

$$M = Px_1 \implies P = M/x_1 \tag{8}$$

The center of mass of the distributed load x_m can be obtained as

$$x_1 = \frac{\int_0^{L_b} rp_x(r)\mathrm{d}r}{\int_0^{L_b} p_x(r)\mathrm{d}r} \tag{9}$$

It has been observed that for small changes in wind speed or rotor speeds x_1 is constant. Therefore, a constant x_1 is assumed to estimate of the point load P from the measured blade root moments. The forces on the blades, the tower and the platform is then approximated as

$$\tilde{\mathbf{f}} = \begin{cases} P_1 \frac{x_1}{x_2}\phi(x_2) \\ P_2 \frac{x_1}{x_2}\phi(x_2) \\ P_3 \frac{x_1}{x_2}\phi(x_2) \\ \sum_{i=1}^3 P_i \\ H_{hub} \sum_{i=1}^3 P_i \end{cases} \tag{10}$$

where, $\tilde{\mathbf{f}}$ is the vector of approximated forces and moments on the blades, the tower and the platform; and P_i is the approximated point load on the i^{th} blade. In the above equation x_2 is obtained as

$$x_2 = \frac{\int_0^{L_b} rp_x(r)\phi(r)\mathrm{d}r}{\int_0^{L_b} p_x(r)\phi(r)\mathrm{d}r} \tag{11}$$

The terms of equation (6) are given as

$$\begin{aligned} &\mathbf{A} = \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ \mathbf{M}^{-1}\mathbf{K} & \mathbf{M}^{-1}\mathbf{C} \end{bmatrix} \qquad \mathbf{B} = \begin{bmatrix} \mathbf{0} \\ \mathbf{M}^{-1}\mathbf{I} \end{bmatrix} \qquad \mathbf{G} = \mathbf{B} \\ &\mathbf{C} = \begin{bmatrix} -\mathbf{M}^{-1}\mathbf{K} & -\mathbf{M}^{-1}\mathbf{C} \end{bmatrix}_{1:3} \qquad \mathbf{D} = \begin{bmatrix} \mathbf{M}^{-1}\mathbf{I} \end{bmatrix}_{1:3} \end{aligned} \tag{12}$$

where the subscripts $_{1:3}$ denote the first three rows of the matrices since it is assumed that only the blade tip accelerations are available as measurement. The vectors $\mathbf{w}$ and $\mathbf{v}$ are the additive white process and measurement noise respectively. The continuous system describe in equation (6) is discretized in MATLAB[21] using the `c2d` function by applying a zero-order hold on the inputs and a sample time of 0.0125 sec. Using the resulting discrete time system a Kalman filter is designed using the `kalman` function in MATLAB[21]. The resulting system is a system that has 10 states, 8 inputs and 13 outputs. The inputs include 3 acceleration measurements and 5 estimations of forces and moments from equation (10). The outputs include 3 filtered acceleration measurement and 10 estimated displacements and velocities that form the estimated state of the reduced DOF system.

3. RESULTS AND DISCUSSION

The 5MW OC3 Hywind turbine, a spar-type FOWT, defined in [20] has been used for numerical purposes. The structural and aerodynamic properties of the tower and the blades are defined in [22]. MATLAB [21] has been used as the simulation platform. A sampling rate of 40 Hz has been used for time integration using the Runga-Kutta 4th order method. Aerodynamic and hydrodynamic loads on the wind turbine are estimated using the Blade Element Momentum (BEM) theory and Morison's equation, respectively. The mooring cables are modelled using MoorDyn [23]. In the following sections, the performance of the Kalman filter and controller is presented. The load case investigated in this paper, TurbSim [24] is used to generate a 3D wind field with a hub height mean wind speed of 19 m/s with a Normal Turbulence Model. The Pierson-Moskowitz spectrum with a wave height of 2.25 m and a wave period of 6.25 sec is used to generate the wave kinematics.

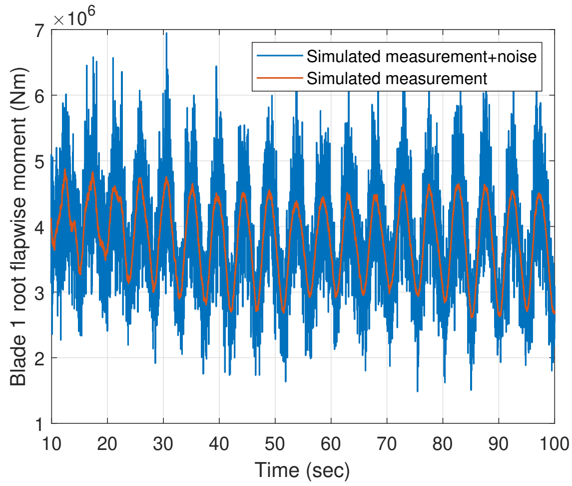

Figure 2. Simulated blade root bending moment corrupted by artificial white noise

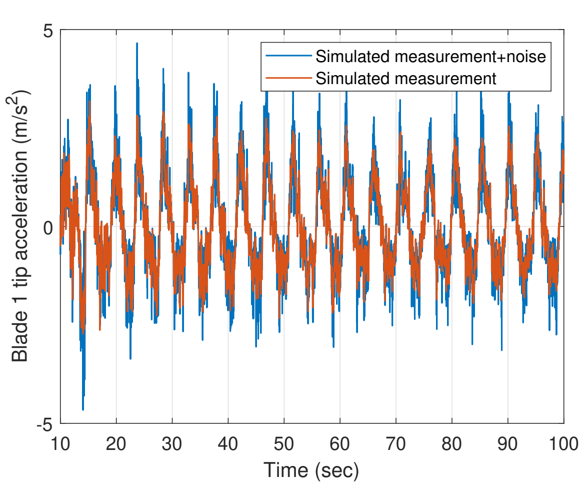

Figure 3. Simulated blade tip acceleration corrupted by artificial white noise

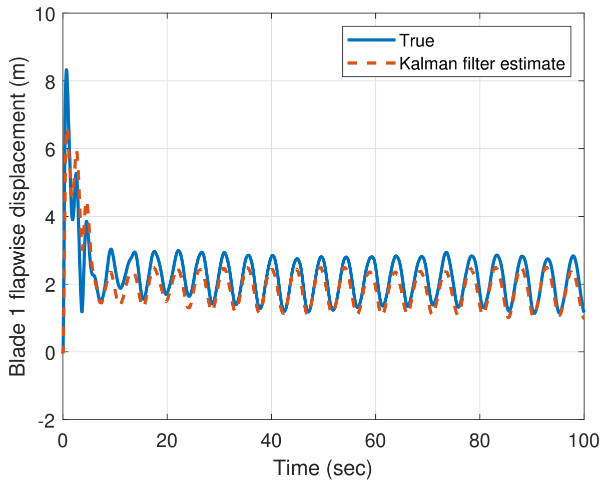

Figure 4. Comparison of the true state and the estimated state from the Kalman filter

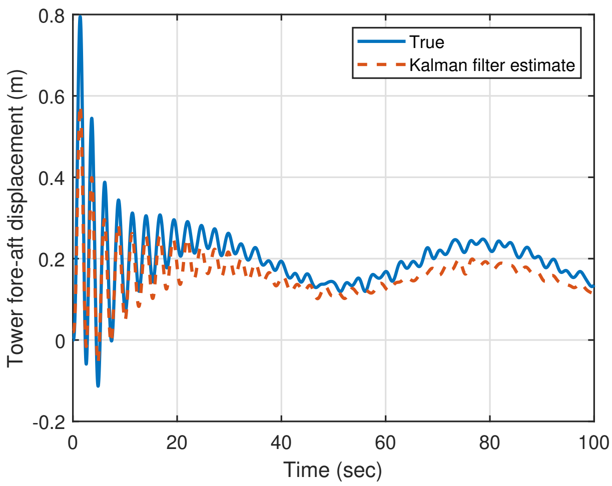

Figure 5. Comparison of the true state and the estimated state from the Kalman filter

3.1. Performance of the Kalman filter

The Kalman filter is designed with the following selection of the plant noise covariance matrix $\mathbf{M}$ and the measurement noise covariance matrix $\mathbf{N}$

$$
\begin{aligned}
\mathbf{M} &= \begin{bmatrix} 6e13 & 0 & 0 & 0 & 0 & \\ & 0 & 8e9 & 0 & 0 & 0 \\ & 0 & 0 & 1.5e8 & 0 & 0 \\ & 0 & 0 & 0 & 1.5e8 & 0 \\ & 0 & 0 & 0 & 0 & 1.5e8 \end{bmatrix} \\
\mathbf{N} &= 0.1 \times \mathbf{I}_{3\times 3}
\end{aligned} \tag{13}
$$

For numerical investigation, the simulated measurements are artificially corrupted with white noise. The approximated loads and moments are corrupted with a standard deviation of 14% error in each measurement, and a standard deviation of 31% error corrupts the acceleration measurements. The simulated blade one root moment with and without the additive noise is

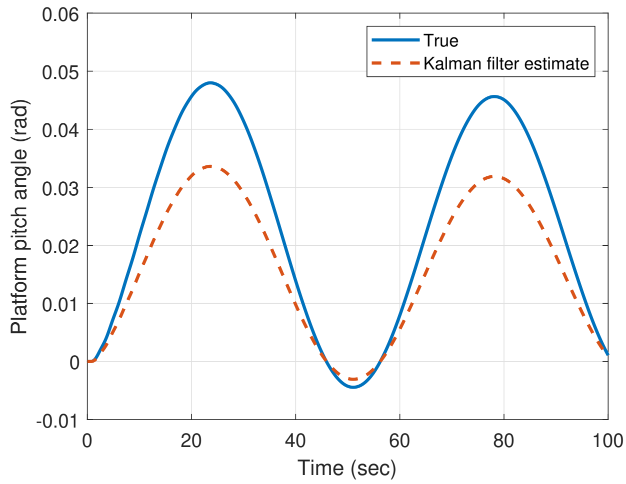

Figure 6. Comparison of the true state and the estimated state from the Kalman filter

shown in Figure 2 and the simulated blade one tip acceleration with and without the additive noise is shown in Figure 3. The results of blades 2 and 3 are similar. The state prediction obtained from the Kalman filter is summarized in Figure 4 through Figure 6. It can be observed that the estimation of the blade and tower displacements obtained from the Kalman filter in Figure 4 and Figure 5 are satisfactory. The estimation of the platform pitch rotation is slightly poor, as shown in Figure 6. However, the impact of this estimation error is insignificant on the controller performance, as shown in the next section.

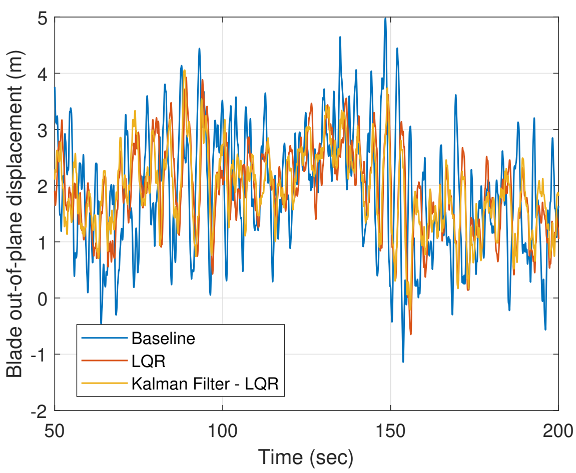

Figure 7. Blade out-of-plane displacement

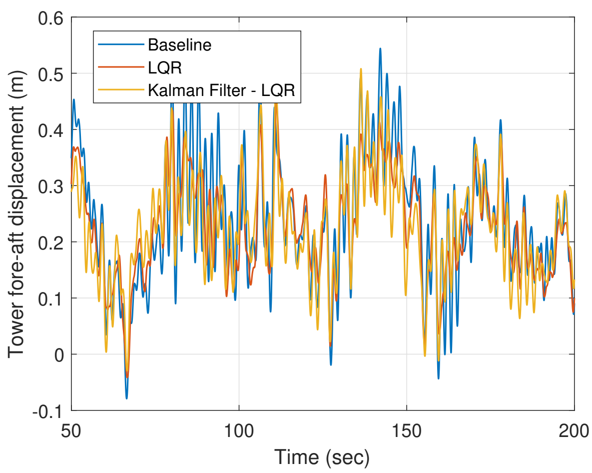

Figure 8. Tower top fore-aft displacement

3.2. Performance of the observer based individual blade pitch controller

The LQ controller is designed with the following selection of the state weight matrix $\mathbf{Q}$ and the input weight matrix $\mathbf{R}$

$$\mathbf{Q} = \begin{bmatrix} \mathbf{Q}_l(1-\rho) & \cdots \\ \cdots & \rho \end{bmatrix} \tag{14}$$

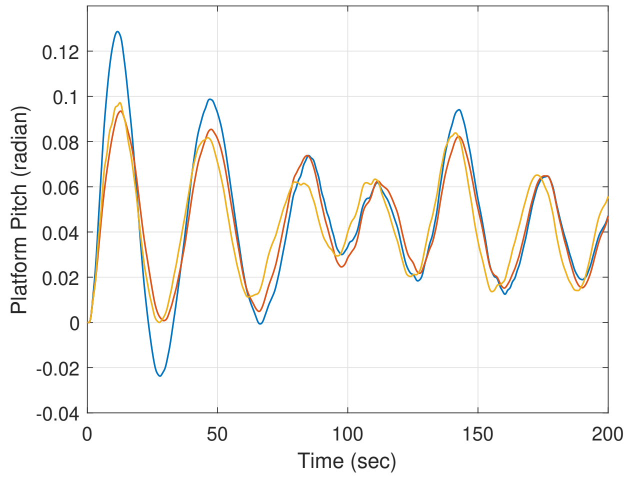

Figure 9. Floating platform pitch rotation

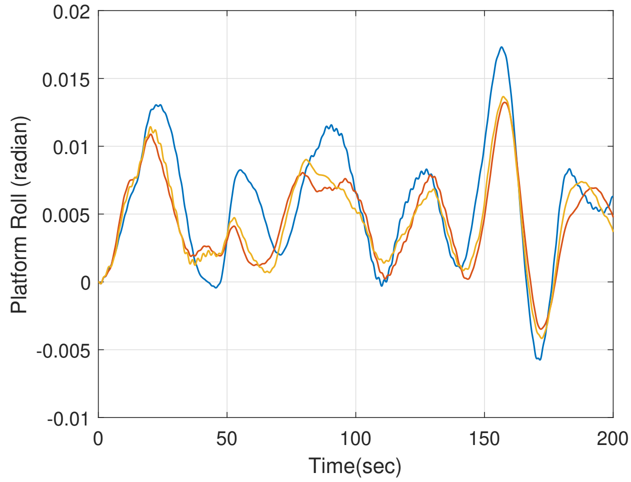

Figure 10. Floating platform pitch rotation

Response	LQR [19]	Kalman Filter-LQR
Blade OOP	28	34
Tower FA	20	19
Platform pitch	12	16
Platform roll	24	22
Rotor speed	29	35

Table 1. Percentage reduction in standard deviation over the baseline controller

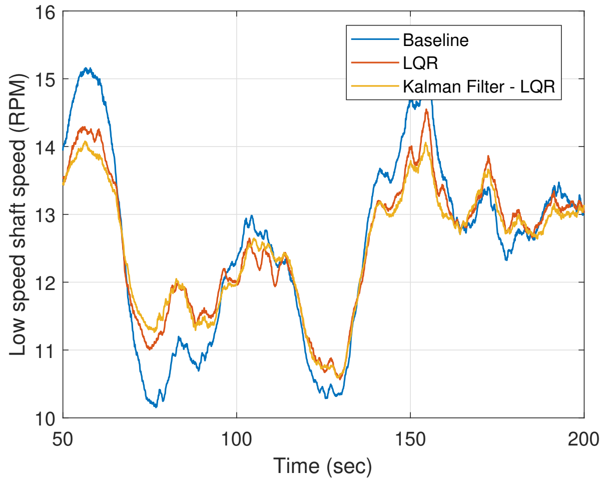

Figure 11. Rotor speed

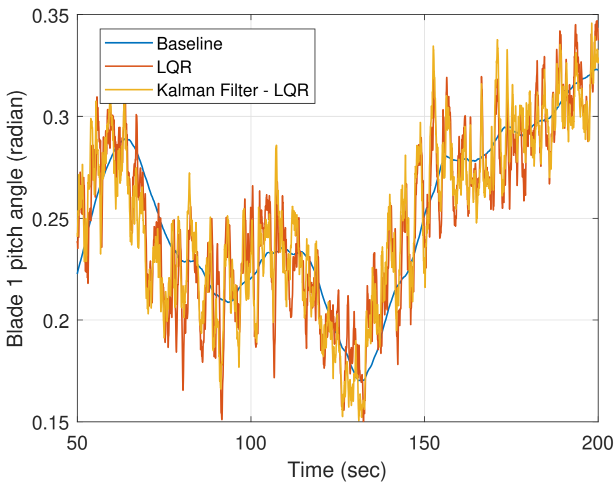

Figure 12. Blade 1 pitch angle

where $\mathbf{Q}_l = 0.001 \times \mathbf{I}_{11\times 11}$. $\mathbf{Q}_l$ is further modified by increasing the weight on the platform and tower degrees of freedom to 1. Pareto optimization of the controller in [19] has shown that the best choice is $\rho = 0.6$. The input weight matrix is simply assumed to be $\mathbf{R} = \mathbf{I}_{3\times 3}$.

The performance of the controller is presented in Figures 7 through 12. The controller presented in this paper is labelled as "Kalman Filter - LQR". The proposed controller is compared against the state-feedback controller proposed by the authors in [19] and is labelled as "LQR" and the baseline controller labelled as "Baseline". It can be observed, in Table 1, that the performance of the proposed controller is similar to the full state-feedback "LQR" controller and is significantly better than the "Baseline" controller in both reducing structural displacements and regulation rotor speed of the FOWT. The similarity of performance to the "LQR" controller demonstrates that the state estimation provided by the Kalman filter is of sufficient accuracy.

4. CONCLUSIONS

An observer based controller has been presented in this paper that combines a Kalman filter for state estimation and a state-feedback IPC. The state-feedback IPC was proposed by the authors previously, and this paper extends its capabilities by designing a Kalman filter that can provide a state estimation from limited and readily available measurements. Only strain gauge and accelerometer measurements are assumed in this paper. The results presented here show that the proposed Kalman filter can satisfactorily estimate the state of the FOWT plant, and successive controller performance is similar to a state-feedback controller. The results presented in this paper show that the promising performance offered by state-feedback IPCs can be realized by using simple and readily available measurements and observers.

It must be noted that even the reduced DOF system used by the authors to design the Kalman filter is nonlinear, and a linearized approximation was used in this work. As part of future work, the authors are investigating an unscented Kalman filter and the associated performance improvements.

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