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Robust Model Predictive Control for Collective Pitch in Wind Energy Conversion Systems

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Abstract: When wind speeds exceed the rated values, wind turbines operate in region 3. In region 3, collective pitch control (CPC) is the main tool to regulate the turbine's speed and generated power. The main challenges that face a CPC design are the modeling uncertainties, constraints on the control actions, and immeasurable system states. A tube-based model-predictive output-feedback controller is proposed here to design a CPC. The proposed controller is an optimal controller that respects constraints and accommodates uncertainties without a need to measure all states. Applications to a typical 5-MW offshore wind turbine show through simulations the superiority of the proposed controller.

Keywords: Collective pitch, pitch control, wind energy, and tube–based model predictive control.

1. INTRODUCTION

Wind energy is one of the fastest growing energy sources worldwide. The installed wind power reached 456 GW in Oct. 2016 (WWEA 2016). The yearly growth rate in 2015 was 16.8%. It was 16.5% in 2014. The environmental and economic merits of utilizing wind energy contributed to this steady growth of the installed wind power. Control systems are utilized to increase extracted power, enhance power quality, and mitigate mechanical stresses to improve the economics of wind energy systems performance.

The wind turbine operation modes rely on the value of the wind speed. Typically, there are three regions of operations. Region 1 is defined by the wind speed below the cut-in value. During the operation in region 1, the wind turbine is utilized to accelerate the rotor for startup. Region 2 is defined by the wind speed below the rated value and above the cut-in value. The control system target during the operation in region 2 is to extract maximum power (Jonkman et al. 2007). Region 3 is defined by the wind speed above the rated value and below the cut-out value. The control system target during the operation in region 3 is to regulate the generator power to its rated value, regulate the generator speed to its rated value and reduce the flapwise moment on the turbine blades. Pitch control is used to achieve the controller objectives in region 3. Pitch control consists of individual pitch control (IPC) and collective pitch control (CPC). Reducing the moment on the blades is the main target of the IPC (Jonkman et al. 2007). Regulating the generator power and speed are the main targets of the CPC.

Several approaches to designing a controller for CPC are addressed in the literature. A robust controller is proposed for the CPC based on H2/H∞ based techniques by (Hassan et al. 2012). A fuzzy-logic-based CPC is designed by (Van, Nguyen & Lee 2015). The generator's power and speed are used as control inputs for the fuzzy-logic-based controller. A common drawback to controllers suggested by (Hassan et al. 2012) and (Van, Nguyen & Lee 2015) is that constraints on pitch angle are not considered. Model predictive control is proposed in the literature for CPC to take care of the pitch constraints. Model predictive control (MPC) is a model based optimizer which uses the system model to predict its future behavior and select the optimal control actions that satisfy constraints. A fuzzy based model predictive controller is proposed to control the collective pitch angle by (Lasheen & Elshafei 2016). A multiple model predictive control is used to maximize energy captured from a wind turbine and to control the collective pitch angle so as to maintain rated output power by (Soliman, Malik & Westwick 2011). However, the work in (Soliman, Malik & Westwick 2011) does not discuss the stability of the nonlinear model. A common drawback to controllers suggested by (Lasheen & Elshafei 2016) and (Soliman, Malik & Westwick 2011) is the use of state observers without considering stability analysis.

Uncertainties have important consequences in the theory of MPC since they affect both the issues of stability and constraints satisfaction. Hence, research efforts on MPC have focused on the robustness issue. One of the promising approaches to handle system uncertainty is to employ the tube –based MPC approach as in (Rawlings & Mayne 2012) and (Goodwin et al. 2014). The tube –based MPC approach can be summarized in four steps. First, an upper bound of the uncertainty and its effect on the system constraints are calculated. Second, based on the effect of the uncertainty on the system constraints, modified system constraints are obtained. Third, MPC is designed to control the system without uncertainty to satisfy the modified constraints (nominal trajectory). Fourth, all possible trajectories of the uncertain system are bounded inside a tube. The center of this tube is the nominal trajectory.

In this work, the proposed controller is designed to overcome the main drawbacks of the CPC in literature. The proposed controller is a tube-based model-predictive output-feedback controller. The proposed controller main advantages are; 1) the ability to handle the pitch constraints by designing a MPC for CPC. 2) It is robust against the uncertainties due to

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adopting a tube based MPC. 3) There is no need to measure all the system states as the proposed controller is an output feedback controller.

This paper is organized as follows: In Section 2, the wind turbine model used is given. In Section 3, a tube-based model-predictive output-feedback controller for CPC is proposed. Simulation results comparing the performance of the proposed controller to a gain-scheduled PI controller are shown in Section 4. Conclusions are stated in Section 5.

2. WIND TURBINE MODEL

In this section, three issues are discussed. First, a simulated wind turbine model is described. Second, the linearized models used to design the robust MPC are obtained. Third, the pitch control command loop is proposed.

2.1. Simulated Wind Turbine Model

Multiple software packages have been developed to simulate the operations of wind turbines by (Larsen & Hansen 2007), (Bottasso & Croce 2009) and (Jonkman et al. 2007). FAST (Fatigue, Aero-dynamics, Structure, and Turbulence) is one of these software packages. It provides a realistic wind turbine model which considers 24 degrees of freedom (DOF). In this paper, FAST is utilized to simulate the operation of a 5-MW, variable speed variable pitch, 3-blades, horizontal axis, offshore wind turbine. More details about the wind turbine model and specifications of the wind turbine used can be found in (Jonkman et al. 2007).

In this paper, a tube-based model-predictive output-feedback controller is designed to control the collective pitch angle. The proposed controller is designed based on a linear model of the wind turbine. Hence, the linearization process is discussed in the following subsection.

2.2. FAST Linearization Process

The design of the proposed controller requires a linearized model. FAST can produce a linearized model at any operating point in the form given in (1). The hub-height wind speed, pitch angle, azimuth angle and generator speed are the variables that specify the operating point. The CPC main purpose is to regulate the generator speed to its rated value while operating in region 3. So, during the linearization process the generator speed should be constant at the rated value. At a certain wind speed, different linearized models are calculated at different azimuth angles. Then, an average model is obtained using Multi-blade Coordinate Transformation (Bir 2008). Furthermore, at steady state, FAST can provide a nominal pitch angle that is associated with a given average wind speed. From this analysis, we conclude that the hub height wind speed is the main variable that characterizes the linearized model. Note that, the controller is designed based on a reduced order model that includes the generator speed and the drivetrain DOF. The full order nonlinear model will be used in the simulations to test the performance of the proposed controller.

The linearized model at a certain wind speed takes the form:

$$\begin{aligned} \dot{x}_i &= A_{ci}x_i + B_{ci}u_{cpc} \\ y &= C_{ci}x_i \end{aligned} \tag{1}$$

where y, u_{cpc} , x_i are the perturbations in the generator speed, CPC action, and the system states calculated at the i^{th} operating point, respectively. The system states are; the drivetrain torsional speed, the drivetrain torsional displacement, and the rotor speed. A_{ci}, B_{ci}, C_{ci} are constant system matrices with proper dimensions.

As discussed before, the main target of the CPC is to keep the generator speed and power at their rated values while the wind speeds varies from 11.4 m/s to 25 m/s (region 3). Seven linearized models are derived with a step of 2 m/s to represent the operating points in region 3. The seven linearized models that cover all the operating points in region 3 could be written in the discrete-time form as:

$$\begin{aligned} x_i(k+1) &= A_{di}x_i(k) + B_{di}u_{cpc}(k) \\ y(k) &= C_{di}x_i(k), \qquad i = 1,2\ldots,7. \end{aligned} \tag{2}$$

where matrices A_{di}, B_{di} can be obtained by discretizing (1) at the i^{th} operating point, Let P be the set given by: $P := (A_d, B_d) := Co\{(A_{di}, B_{di}\ ), i = 1, \ldots, 7\}$, where Co defined as the convex set. Hence, for a certain wind speed the linearized model can be written as in (1) where the pair (A_d, B_d) can be obtained in terms of $(A_{di},\ B_{di})$ and $i = 1, \ldots, 7$.

2.3. Pitch Control Command Loop

The pitch control signal is composed of three components. The first component, u_0, is the pitch angle that corresponds to the operating point according to the average wind speed. This is usually obtained using a look-up table (Provided by FAST). The second component, u_{CPC}, is responsible for CPC and affects all blades similarly. The design of a controller that produces this signal is the focus of this paper. The last component, u_{ipc}, is concerned with each blade individually. Conventional proportional plus integral (PI) controllers are usually used for IPC (Bossanyi 2003). Hence, pitch control command (U_P) can be written as:

$$U_P = u_{ipc} + u_0 + u_{cpc} \tag{3}$$

The pitch control action has a range of change from 0 rad to 1.57 rad and the maximum rate of change is 0.139 rad/sec (Jonkman et al. 2007). The collective pitch constraints can be written as:

$$-u_{ipc}(k) - u_0(k) + u_P^{min} \le u_{cpc}(k) \tag{4}$$

$$-u_{ipc}(k) - u_0(k) + u_P^{max} \ge u_{cpc}(k) \tag{5}$$

$$-\Delta u_{ipc}(k) - \Delta u_0(k) + \Delta u_P^{min} \le \Delta u_{cpc}(k) \tag{6}$$

$$-\Delta u_{ipc}(k) - \Delta u_0(k) + \Delta u_P^{max} \ge \Delta u_{cpc}(k) \tag{7}$$

where u_P^{max} and u_P^{min} are the maximum and minimum allowed values of the pitch angle, respectively. Δu_P^{max} and Δu_P^{min} are the maximum and minimum allowed rates of change of the pitch angle, respectively.

3. TUBE-BASED MODEL PREDICTIVE CONTROL FOR CPC

In this section, the development of the proposed tube-based MPC for CPC is presented. First, the MPC optimization problem is reviewed. Second, tube-based model-predictive output-feedback controller is summarized. Third, the procedure to apply the output feedback tube-based MPC for collective pitching is detailed. Fourth, the CPC control algorithm is presented.

3.1 Model Predictive Control Optimization Problem

Consider a discrete-time constrained linear time-invariant system:

$$\begin{gathered} x(k+1) = A_d x(k) + B_d v(k) \\ y(k) = C_d x(k) \\ \text{Subject to :} \\ y_{min} \le y(k) \le y_{max} \\ v_{min} \le v(k) \le v_{max} \end{gathered} \tag{8}$$

where $x, v,$ and y are the system states, input and output respectively. $y_{max}, y_{min}, v_{max},$ and v_{min} are the maximum and minimum allowable values of the output and input variables, respectively. k is the sampling index. Assuming that the pair (A_d, C_d) is observable, and the pair (A_d, B_d) is controllable. The optimal solution of the problem in (8) based on the MPC vision can be calculated by minimizing the objective function "J" in (9) at each sample.

$$\min_{V \triangleq \begin{Bmatrix} v(k) \\ \vdots \\ v(k+N-1) \end{Bmatrix}^T} \left\{ \begin{array}{c} J(V, x(k)) = x^T(k+N)\bar{Q}x(k+N) + \\ \displaystyle\sum_{i=0}^{N-1} x^T(k+i)Qx(k+i) + v^T(k+i)Rv(k+i) \end{array} \right\}$$

Subject to :

$$\begin{array}{ll} v_{min} \le v(k) \le v_{max} & i = 1, \dots\dots, N \\ y_{min} \le y(k) \le y_{max} & i = 1, \dots\dots, N \\ x(k+i+1) = A_d x(k+i) + B_d v(k+i) & i \ge 0 \\ y(k+i) = C_d x(k+i) & i \ge 0 \end{array} \tag{9}$$

where N is the prediction horizon, $x(k+i)$ is the vector of predicted states at instant k. At each instant, the optimal trajectory $V = [v^*(k) \quad v^*(k+1) \quad \dots \quad v^*(k+N-1)]^T$ is calculated by minimizing (9). Based on the receding horizon policy, the first row of the optimal sequence is applied to the system. The predicted states are calculated as:

$$X_p = Px(k) + MV \tag{10}$$

where $V = [v(k) \quad v(k+1) \quad \dots \quad v(k+N-1)]^T$,

$$X_p = \begin{bmatrix} x(k+1) \\ x(k+2) \\ \vdots \\ x(k+N) \end{bmatrix}, P = \begin{bmatrix} A_d \\ A_d^2 \\ \vdots \\ A_d^N \end{bmatrix}, M = \begin{bmatrix} B_d & 0 & \dots & 0 \\ A_d B_d & B_d & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ A_d^{N-2} B_d & \dots & \dots & 0 \\ A_d^{N-1} B_d & \dots & A_d B_d & B_d \end{bmatrix}.$$

Using (10), the MPC optimization problem given in (9) can be reformulated as:

$$J(x(k)) = \min_V \left\{ \frac{1}{2} V^T H V + x^T(k) F V \right\} + \frac{1}{2} x^T(k)\, Y x(k) \tag{11}$$
$$\text{s.t. } EV \le w + Gx(k)$$

where G, w, E are constant matrices that can be computed from the constraints in (8). $H = 2(M^T\tilde{Q}M + \tilde{R}), F = M^T\tilde{Q}P,$ and $Y = 2(P^T\tilde{Q}P + Q)$. where $\tilde{R},$ and $\tilde{Q}$ can be computed as follows:

$$\tilde{R} = \begin{bmatrix} R & 0 & \dots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & R & 0 \\ 0 & \dots & 0 & R \end{bmatrix}, \tilde{Q} = \begin{bmatrix} Q & 0 & \dots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & Q & 0 \\ 0 & \dots & 0 & \bar{Q} \end{bmatrix}.$$

3.2 Tube-based Model-Predictive Output Feedback Controller

In this subsection, the analysis of the tube-based model-predictive output-feedback controller is discussed (Goodwin et al. 2014). Consider the following discrete-time constrained uncertain linear time-invariant system (uncertain system):

$$\begin{gathered} x(k+1) = A_d x(k) + B_d u(k) + w \\ y(k) = C_d x(k) \\ \text{Subject to :} \\ x_{min} \le x(k) \le x_{max} \\ u_{min} \le u(k) \le u_{max} \\ \Delta u_{min} \le \Delta u(k) \le \Delta u_{max} \\ w \in W \end{gathered} \tag{12}$$

where u is the control action and w is the additive disturbance that affects the system. W is the compact set that contains all possible disturbances. $x_{max}, x_{min}, \Delta u_{max}, \Delta u_{min}, u_{max}, u_{min}$ are the maximum and minimum allowable values of states, the rate of change of the input, and input variables, respectively. Assume that the pair (A_d, C_d) is observable, the pair (A_d, B_d) is controllable, the system states are not measured, the output is measured, and the disturbance is bounded and unknown. The main objective of the tube –based MPC is to design a model predictive control to ensure that the uncertain closed loop system is stable, and all possible trajectories of the uncertain system lie in a tube that satisfies the constraints on the states, input, and rate of change of the input. The main idea behind the tube-based MPC is to design a MPC for the system given in (12) without disturbance (nominal system) with tighter constraints. The tighter constraints are calculated based on the upper bound of the disturbance (W). Let the nominal system take the form:

$$\begin{gathered} x_n(k+1) = A_d x_n(k) + B_d v(k) \\ y_n(k) = C_d x_n(k) \\ \text{Subject to :} \\ x_{n_{min}} \le x_n(k) \le x_{n_{max}} \\ v_{min} \le v(k) \le v_{max} \\ \Delta v_{min} \le \Delta v(k) \le \Delta v_{max} \end{gathered} \tag{13}$$

where $A_d, B_d,$ and C_d are the same as in (12) and (13). $y_n, x_n,$ and v are the nominal system output, state and input, respectively. $x_{n_{max}}, x_{n_{min}}, \Delta v_{max}, \Delta v_{min}, v_{max}, v_{min,}$ are the maximum and minimum allowable values of the states, rate of change of the input and input variables of the nominal system, respectively. To estimate the system states, a simple observer is used as.

$$\hat{x}(k+1) = A_d \hat{x}(k) + B_d u(k) + L(y(k) - \hat{y}(k)) \tag{14}$$
$$\hat{y}(k) = C_d \hat{x}(k), A_l = A_d - LC_d$$

where $\hat{x}$ is the observer states vector, L is the observer gain. L is selected to make the matrix $A_l = A_d - LC_d$ stable. From (12) and (14) the state estimation error vector ($\tilde{x} = x - \hat{x}$) satisfies.

$$\tilde{x}(k+1) = A_l\tilde{x}(k) + w \tag{15}$$

Let the control action, u, to the uncertain system, given in (12), be defined as:

$$u = v + K_t(\hat{x} - x_n) \tag{16}$$

where v is the control action of the nominal system. $\hat{x}$, x_n are the estimated and nominal states, respectively. K_t is a state feedback gain that makes $A_k = A_d + B_dK_t$ stable. With the control action given in (16), the closed loop observer states satisfy:

$$\begin{aligned}\hat{x}(k+1) = A_d\hat{x}(k) + B_dv(k) + B_dK_t(\hat{x} - x_n)\\ + LC_d\tilde{x}\end{aligned} \tag{17}$$

Let $e \stackrel{\text{def}}{=} \hat{x} - x_n$. From (13) and (17), the error between the estimated states and the nominal states (e) satisfies the difference equation:

$$e(k+1) = A_ke(k) + LC_d\tilde{x}, \qquad A_k = A_d + B_dK_t \tag{18}$$

By definition, the observer states differ from the nominal states by e ($\hat{x} = e + x_n$). The actual states differ from the estimated states by $\tilde{x}(x = \tilde{x} + \hat{x})$ so that,

$$x = \tilde{x} + e + x_n \tag{19}$$

From (19), the state constraints of the nominal system (constraints on x_n) can be calculated based on the state constraints of the uncertain system (constraints on x), the upper bound of e, and the upper bound of $\tilde{x}$. From (16), the control action constraint of the nominal system (constraints on v) can be calculated based on the control action constraints of the uncertain system (constraints on u), the state feedback gain K_t and the upper bound of e. The tighter constraints on the nominal system can be formulated as:

$$\begin{aligned}x_{n_{max}} &= x_{max} - S - \tilde{S}\\ v_{max} &= u_{max} - K_tS\\ \Delta v_{max} &= \Delta u_{max} - K_t\Delta S\end{aligned} \tag{20}$$

where S is the upper bound of e (can be calculated from (18)) and $\tilde{S}$ is the upper bound of $\tilde{x}$ (can be calculated from (15)).

The design of an MPC for the system without additive disturbance is defined in (13). It satisfies the modified constraints in (20). Applying the control law given in (16) to the uncertain system given in (12), we conclude that the uncertain system is stable and satisfies the constraints.

3.3 Tube-based Model-Predictive Output-Feedback Controller for CPC

In this subsection, the parametric uncertainty for the CPC problem given in (2) with the constraints given in (4)-(7) is reformulated to be in the form of the uncertain system with an additive disturbance as in (12).

The uncertain system given in (2) can be reformulated as:

$$\begin{aligned}x(k+1) &= A_{d4}x(k) + B_{d4}u_{cpc}(k) + w\\ w &:= (A_d - A_{d4})x + (B_d - B_{d4})u_{cpc}\end{aligned} \tag{21}$$

where A_d, B_d are as defined in (2). x is the uncertain system states. A_{d4}, B_{d4} are the matrices at wind speed of 18 m/s (mid-point model). However, the system given in (2) has constraints on the rate of change of the control action (Δu_{cpc}) that does not appear on the additive disturbance w. Hence, an augmented model is used to take care of the constraints on rate of change of the control action.

The uncertain system given in (2) can be reformulated as:

$$\begin{bmatrix} x(k+1) \\ u_{cpc}(k) \end{bmatrix} = \begin{bmatrix} A_d & B_d \\ 0 & 1 \end{bmatrix}\begin{bmatrix} x(k) \\ u_{cpc}(k-1) \end{bmatrix} + \begin{bmatrix} B_d \\ 1 \end{bmatrix}\Delta u_{cpc} \tag{22}$$

Assume that, the linearized model at the mid-point (model at wind speed of 18m/s) is the nominal system. Hence, the nominal system takes the form:

$$\begin{bmatrix} x_4(k+1) \\ v(k) \end{bmatrix} = \begin{bmatrix} A_{d4} & B_{d4} \\ 0 & 1 \end{bmatrix}\begin{bmatrix} x_4(k) \\ v(k-1) \end{bmatrix} + \begin{bmatrix} B_{d4} \\ 1 \end{bmatrix}\Delta v \tag{23}$$

The uncertain system in (22) can be rewritten as:

$$\begin{aligned}\begin{bmatrix} x(k+1) \\ u_{cpc}(k) \end{bmatrix} = \begin{bmatrix} A_{d4} & B_{d4} \\ 0 & 1 \end{bmatrix}\begin{bmatrix} x(k) \\ u_{cpc}(k-1) \end{bmatrix}\\ + \begin{bmatrix} B_{d4} \\ 1 \end{bmatrix}\Delta u_{cpc} + w\end{aligned} \tag{24}$$

From (22) and (24), the additive disturbance (w) can be calculated as:

$$\begin{aligned}w := (A_d - A_{d4})x + (B_d - B_{d4})u_{cpc}\\ +(B_d - B_{d4})\,\Delta u_{cpc}\end{aligned} \tag{25}$$

The upper bound of the additive disturbance w is calculated using the linearized models given in (2) and the constraints given in (4)-(7). In this work, the procedure described in subsection 3.2 is used to control the uncertain system given in (24). As discussed before, the nominal system is the system given in (23). The tighter constraints can be calculated as:

$$-u_{ipc}(k) - u_0(k) + u_P^{min} - K_tS \le v_{cpc}(k) \tag{26}$$

$$-u_{ipc}(k) - u_0(k) + u_P^{max} - K_tS \ge v_{cpc}(k) \tag{27}$$

$$-\Delta u_{ipc}(k) - \Delta u_0(k) + \Delta u_P^{min} - K_t\Delta S \le \Delta v_{cpc}(k) \tag{28}$$

$$-\Delta u_{ipc}(k) - \Delta u_0(k) + \Delta u_P^{max} - K_t\Delta S \ge \Delta v_{cpc}(k) \tag{29}$$

where v_{cpc} is the CPC action of the nominal system. The uncertain CPC action u_{cpc} is calculated as given in (16).

3.4 The Control Algorithm

The proposed controller is a tube-based model-predictive output-feedback controller. The control algorithm consists of; off-line calculations and on-line calculations. Fig. 1 shows the development of the pitch control command.

<u>Off-line calculations:</u>

- The continuous state space linearized model (A_{ci}, B_{ci}, C_{ci}) is calculated at different operating points as in (1).
- The discrete state space model (A_{di}, B_{di}, C_{di}) is calculated using an appropriate sampling interval.
- The parametric uncertain model is constructed as given in (2).

- The parametric uncertainty of the wind turbine model is reformulated as an additive disturbance, and hence, the boundary of the disturbance w is calculated as in (25) using the CPC constraints given in (4)-(7).
- The tighter constraints are calculated based on the nominal system as in (23), (26)-(29).
- The constraints given in (26)-(29) are reformulated to be the form given in (11).
- For the nominal model (corresponding to a wind speed of 18 m/s), the matrices H, F are calculated as in (11), i.e. $\mathrm{A_d}$ and $\mathrm{B_d}$ are the matrices at the midpoint (18m/s).

<u>Online calculations at each sample:</u>

- Estimate the immeasurable system states.
- Solve the optimization problem given in (11).
- The first element of the optimal control action v, calculated using the previous step, is applied to the nominal system.
- The error signal between the estimated system states and the nominal system states is calculated.
- The CPC command of the uncertain system is calculated as given in (16).
- The total control command is calculated as in (3).

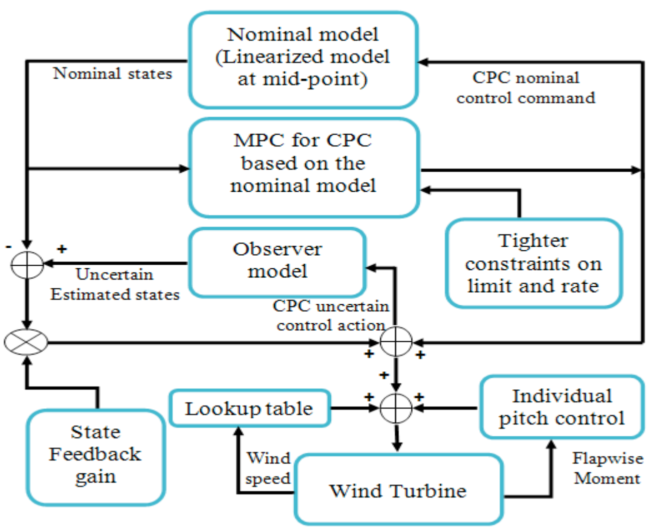


Fig.1. Pitch control loop.

4. SIMULATION RESULTS

In this section, three main points are discussed. First, the wind turbine model used to test the performance of the proposed controller is discussed. Second, numerical results comparing the proposed controller performance versus the gain-scheduled PI controller are shown. Third, the proposed controller is tested against an extended range of wind speed variations.

4.1 Simulated FAST Model

To get practical results, two important tests in FAST model are considered. First, as discussed in subsection 2.1, the proposed controller is designed based on a reduced order model. However, the simulation results are obtained by enabling all the 24 DOF provided by FAST. Second, stochastic wind profiles can be generated using a software package such as TurbSim (Kelley & Jonkman 2007). TurbSim is used to generate a 2-dimensional wind profile that covers the whole turbine body including its tower. Fig. 2 depicts a stochastic wind profile that will be applied at the hub height to the model of the wind turbine under study.

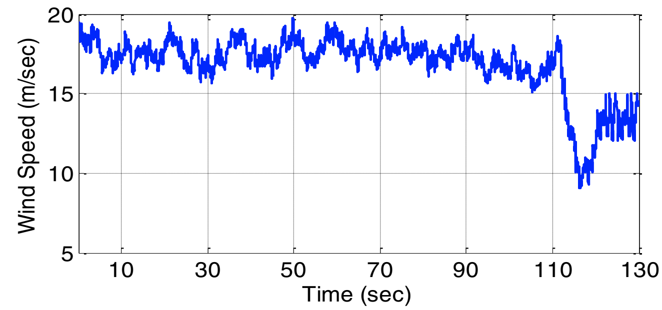


Fig.2. Hub height wind speed profile

4.2 Numerical Results

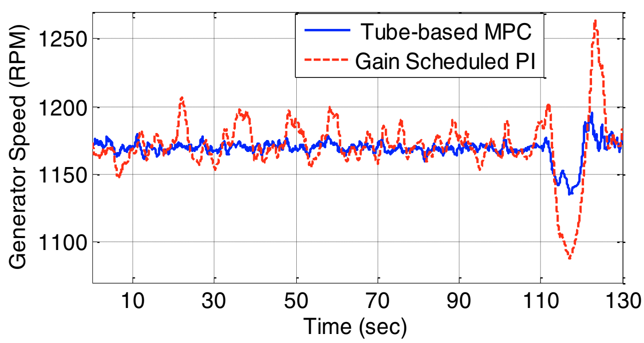
In this subsection, the proposed controller performance is compared to that of the gain scheduled PI controller (Jonkman et al. 2007). The wind speed pattern shown in Fig. 2 is applied to test the controllers' performance. The results are reported in Fig. 3. They include data plots of the generator power, the generated speed, and the flapwise moments. Analysis of the results is given in Table 1. It is clear that the proposed controller suppresses the fluctuations in speed, power, and flapwise moments. This is reflected in Table 1 by the standard deviations' values. Compared to the gain-scheduled PI controller, the proposed controller reduces the standard deviations in speed, power, and flapwise moments by 72.9%, 55%, and 2.6%, respectively. The proposed controller also enhances the system's regulation. Compared to the gain scheduled PI controller, the proposed controller reduces the regulation error in the power, by 1%. It is also noted that the proposed controller has the lowest maximum flapwise moment as compared to the gain scheduled PI controller. The proposed controller reduces the maximum flapwise moment by 5.8%.

4.3 Wind Speed Variations

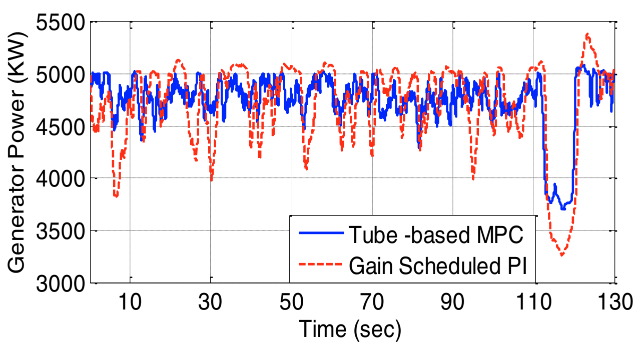
Wind speeds may vary above and below the rated value. Consequently, the controller's target must shift from maximizing extracted power while working in region 2 to regulating the extracted power at the rated value while working in region 3. This transferring issue can be solved through the employment of a decentralized controller. The proposed pitch controller is designed to work in region 3. So, we should make sure that if the wind speed drops under the rated value the pitch control action should automatically disconnect. As shown in Fig. 2, the wind speed pattern used involves wind speeds below the rated value in the interval 115 sec to 120 sec. The pitch control action throughout this interval is equal to zero as shown in Fig. 4. This shows that the proposed controller automatically disconnect while working in region 2 and any other controller can be connected to extract the maximum power from the wind turbine. Moreover, the wind speed pattern used returned to region 3 in the period of 120 sec to 130 sec. Fig. 3 shows the smooth transition of the proposed controller compared to the gain scheduled PI controller.

5. CONCLUSIONS

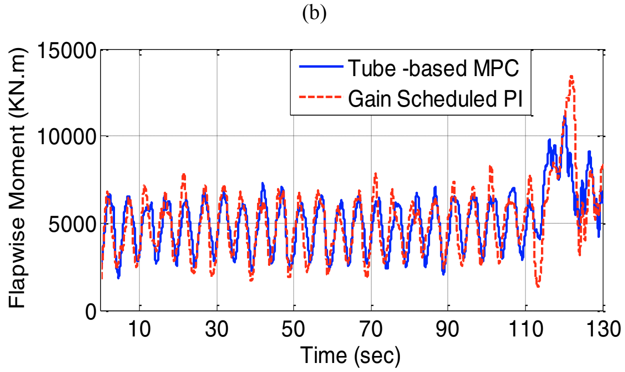
This paper has addressed the design of a tube-based model-predictive output-feedback controller for collective pitching of wind turbines. The proposed controller has two advantages. First, it is robust against model uncertainty by adopting a tube based approach. Second, it takes into account the observer design. The proposed controller is coupled with individual pitch control for a mechanical load reduction. The simulations have been carried using FAST models for a 5-MW offshore wind turbine. The proposed controller's performance has been compared to a gain-scheduled PI controller. The results show that the proposed controller achieves significant enhancements in generator power, speed regulation, and reduction of the mechanical loads.



(a)



(b)



(c)

Fig.3. Comparison of different system variables when using a gain-scheduled PI controller and the proposed controller: (a) generator speed (b) generator power (c) flapwise moment on the first blade.

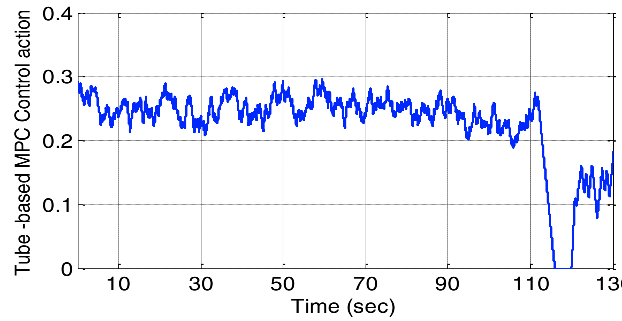


Fig. 4 Pitch command on the first blade

Table 1 Analysis of the simulation results in Fig. 3.

		Gain scheduled PI	Proposed Controller
Generator speed (rpm)	Max (abs (error))	32.56	14.07
	Mean	1171	1170.5
	Std (error)	10.55	2.85
Electric power (KW)	Max (abs (error))	1177	711.44
	Mean	4752	4801
	Std (error)	298.43	134.24
Flap wise moment (KN.m)	Max	7587	7145
	Mean	4732	4757
	Std	1443	1406

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