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ACTIVE FAULT TOLERANCE CONTROL OF A WIND TURBINE SYSTEM USING AN UNKNOWN INPUT OBSERVER WITH AN ACTUATOR FAULT

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This paper proposes a fault tolerant control scheme based on an unknown input observer for a wind turbine system subject to an actuator fault and disturbance. Firstly, an unknown input observer for state estimation and fault detection using a linear parameter varying model is developed. By solving linear matrix inequalities (LMIs) and linear matrix equalities (LMEs), the gains of the unknown input observer are obtained. The convergence of the unknown input observer is also analysed with Lyapunov theory. Secondly, using fault estimation, an active fault tolerant controller is applied to a wind turbine system. Finally, a simulation of a wind turbine benchmark with an actuator fault is tested for the proposed method. The simulation results indicate that the proposed FTC scheme is efficient.

Keywords: wind turbine system, linear parameter varying system, fault tolerant control, unknown input observer.

1. Introduction

Due to a large number of consumption of fossil resources and the increasing awareness of environmental protection, wind energy as a sustainable renewable energy has been attracted more and more attention. In the last decade, the installed capacity of wind energy has been growing rapidly and it becomes one of the most important energies in the family of renewable energies (Khare *et al.*, 2016). A wind turbine system is nonlinear, high-order and easy to be affected by disturbances. With the increasing power of a standard wind turbine system, the system becomes more and more complicated and the nonlinearity of the wind turbine system gets increasingly prominent (Jonkman *et al.*, 2009). The demand for performance and reliability in the closed-loop system becomes stronger.

In the wind turbine system, the components are challenged by a variety of extreme climates and are subject to faults. If there is no action to be taken in a fault situation, the system performance would be degraded or it would even have to stop. In order to handle faults caused by sensors, actuators or system components, many fault detection and isolation (FDI) and fault tolerant control (FTC) techniques have been put forward (Georges *et al.*, 2011; Chen and Saif, 2006; Kamal and Aitouche, 2013; Simani *et al.*, 2015; Boulkroune *et al.*, 2013). Fault tolerant control schemes can maintain stability and acceptable performance of the system and major economic losses can be avoided. In active fault tolerant control systems, faults can be estimated and compensated. Odgaard *et al.* (2009) list over ten kinds of faults in a benchmark model of wind turbine systems and these faults cover different parts of a wind turbine, including sensors, actuators and components.

The main problem of fault tolerant control in a wind turbine system is that it is difficult to model the entire system because of its strong nonlinearity and uncertainty.

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Besides, the uncontrolled wind with turbulence becomes the most important source of disturbances and affects the output performance. In recent years, many results have been reported on FTC for wind turbine systems. Kamal *et al.* (2012; 2014) present a robust fuzzy fault tolerant control of wind energy conversion systems subject to sensor faults. Also, in the works of Georg and Schulte (2014; 2013), a Takagi–Sugeno fuzzy sliding mode observer with a weighted switching action is considered with fault diagnosis for wind turbines. Simani and Castaldi (2014) present an active actuator fault tolerant control based on adaptive filters obtained by the nonlinear geometric approach.

Using virtual sensors/actuators to handle real sensor and actuator faults and an interval observer, FDI and FTC of wind turbines are developed by Blesa *et al*. (2014). In the work of Shi and Patton (2015), an active fault tolerant control approach to an offshore wind turbine model is presented to deal with sensor and actuator faults. Based on linear matrix inequality (LMI) techniques, a robust and fault-tolerant linear parameter-varying (LPV) control scheme is developed for the LPV system by Sloth *et al*. (2011). In addition, using fuzzy logic theory, a fault tolerant control based on data-drive for wind turbine benchmark is presented by Simani and Castaldi (2012). Generally, these approaches have some advantages to deal with certain problems of wind turbine systems.

In this paper, an active fault tolerant control scheme for a wind turbine system with an actuator fault is developed. Due to the advantage of the LPV model to describe some nonlinear systems, the wind turbine system will be modeled in LPV form by using a benchmark model (Odgaard *et al.*, 2009; 2013). Based on this LPV model, an unknown input observer (UIO) is designed to estimate the state variables and fault signals. In the UIO, the estimation of the original state becomes associated with a transformed state and the state estimates can be calculated from the transformed state. By solving LMIs and linear matrix equalities (LMEs), the solution of the UIO can be obtained. As for disturbance and actuator faults, the convergence of the UIO is also analysed using Lyapunov and H_∞ theories. The proposed method can estimate not only a constant fault, but also those with a bounded derivative. Finally, a wind turbine system with disturbance and actuator faults is utilized to illustrate the performance. From the results, it is clear that the proposed UIO and fault estimation algorithm are efficient.

Therefore, the main objective of this paper is to detect and compensate, in the control loop, actuator pitch and torque faults of the wind turbine system based on the unknown input observer to deal with nonlinearity in the fault detecting and diagnosis approach. The principle of the proposed method is to use an LPV model to represent nonlinear dynamics of the WTS. The advantage of LPV systems is that they make it possible to use linear-like control theory. LMI methods have become very powerful, in many areas, including network control design (Armeni *et al.*, 2009). Control systems subject to faults which can be caused by sensors and actuators are an important issue in fault tolerant control system design to keep the system stable and to maintain acceptable performances when failures occur. The results of this paper prove that the proposed method is able to (i) detect and isolate actuator faults of the wind turbine benchmark, and estimate their amplitude, (ii) provide a control law able to compensate the fault effect.

This paper is organized as follows. In Section 2, problem formulation and preliminaries are presented. Design and analysis of the UIO are provided in Section 3. A benchmark model of the wind turbine system is discussed in Section 4. Simulation results are presented in Section 5. Finally, some conclusions are given in Section 6.

2. Problem formulation and preliminaries

Consider a nonlinear system with the input, output and unknown input vectors $u \in \mathbb{R}^m, y \in \mathbb{R}^p$ and $d \in \mathbb{R}^l$, respectively. Assume that it can be expressed in LPV form as

$$\begin{aligned} \dot{x}(t) &= A(\alpha)x(t) + B(\alpha)u(t) \\ &\quad + D(\alpha)d(t) + Ff(t), \\ y(t) &= Cx(t), \end{aligned} \tag{1}$$

where $x \in \mathbb{R}^n$ is the state vector, F is the fault matrix, $A(\alpha) \in \mathbb{R}^{n\times n}, B(\alpha) \in \mathbb{R}^{n\times m}, C \in \mathbb{R}^{p\times n}, D(\alpha) \in \mathbb{R}^{n\times l}$ are matrices dependent on α, a time varying parameter assumed to be bounded. Here $d(t)$ and $f(t)$ are the disturbance and the fault vector, respectively. We assume that the matrices $A(\alpha)$, $B(\alpha)$, $D(\alpha)$ can be written as polytopic ones and are given by

$$\begin{aligned} A(\alpha) &= \sum_{i=1}^{r} \rho_i A_i, \\ B(\alpha) &= \sum_{i=1}^{r} \rho_i B_i, \\ D(\alpha) &= \sum_{i=1}^{r} \rho_i D_i, \end{aligned} \tag{2}$$

where ρ_i are weights of the LPV subsystem,

$$\sum_{i=1}^{r} \rho_i = 1, \qquad 0 \le \rho_i \le 1. \tag{3}$$

The polytopic representation of the system (1) becomes

$$\begin{aligned} \dot{x}(t) &= \sum_{i=1}^{r} \rho_i (A_i x(t) + B_i u(t) + D_i d(t)) \\ &\quad + Ff(t), \\ y(t) &= Cx(t), \end{aligned} \tag{4}$$

where A_i, B_i, D_i are time invariant matrices. Assume that the matrices D_i have full column rank.

Assumption 1.

1. The pair (A_i, C) is observable for $i = 1, \dots, r$.

2. The matrix C is of full row rank. D_i is also of full column rank, $i = 1, 2, \dots, r$.

3. The disturbance $d(t)$ and fault $f(t)$ are functions with a bounded first derivative.

3. Design and analysis of active fault tolerant control for an LPV system

In this section, we will design an unknown input observer for LPV system. The convergence of the unknown input observer will be analyzed.

3.1. Design of the unknown input observer. For the system (4), the unknown input observer can be written as

$$\begin{aligned} \dot{z}(t) &= \sum_{i=1}^{r} \rho_i (N_i z(t) + G_i u(t) + L_i y(t)) \\ &\quad + T\hat{f}(t), \\ \hat{x}(t) &= z(t) - Ey(t), \\ \hat{f}(t) &= \Gamma S(r_e + \sigma \int r_e \,\mathrm{d}t), \end{aligned} \tag{5}$$

where $\hat{x}(t)$ and $\hat{f}(t)$ are respectively the state estimate vector and the fault vector, $z(t)$ is a state vector related to $\hat{x}(t)$, $r_e = y - \hat{y} = y - C\hat{x}$ is a residual, $N_i, G_i, L_i, E, T, S, \Gamma$ are unknown matrices of appropriate dimensions. They satisfy the following conditions:

$$\begin{aligned} N_i &= MA_i - K_i C, \\ G_i &= MB_i, \\ L_i &= K_i(I_1 + CE) - MA_i E, \\ MD_i &= 0, \\ MF &= T. \end{aligned} \tag{6}$$

Defining the state error vector $e(t) = x(t) - \hat{x}(t)$, we obtain

$$e(t) = (EC + I_2)x(t) - z(t) \triangleq Mx(t) - z(t), \tag{7}$$

where $M = EC + I_2$. I_1 and I_2 are identity matrices of the appropriate dimensions.

If the conditions (6) are satisfied and the fault estimation error is defined as $\tilde{f}(t) = f(t) - \hat{f}(t)$, the derivative of the error becomes

$$\begin{aligned} \dot{e}(t) &= M\dot{x}(t) - \dot{z}(t) \\ &= \sum_{i=1}^{r} \rho_i [N_i e(t) + T\tilde{f}(t) \\ &\quad + (MA_i - N_i M - L_i C)x(t) \\ &\quad + (MB_i - G_i)u(t) + MD_i d(t) \\ &\quad + (MF - T)f(t)]. \end{aligned} \tag{8}$$

Defining a matrix $K_i = L_i + N_i E$, we obtain

$$\begin{aligned} &MA_i - N_i M - L_i C \\ &\quad = MA_i - N_i M - (K_i - N_i E)C \\ &\quad = (MA_i - K_i C)(I_2 - M + EC) = 0. \end{aligned} \tag{9}$$

Substituting (9) into (8), the error dynamic equation can be simplified as

$$\dot{e}(t) = \sum_{i=1}^{r} \rho_i (N_i e(t) + T\tilde{f}(t)). \tag{10}$$

3.2. Fault estimation and convergence analysis. First, two auxiliary results are introduced

Lemma 1. (Zhang *et al.*, 2008) *Given a scalar μ and a positive definite symmetric matrix P_1, the following equality holds:*

$$2x^T y \le \frac{1}{\mu} x^T P_1 x + \mu y^T P_1^{-1} y, \quad x, y \in \mathbb{R}^n. \tag{11}$$

Lemma 2. *If there exist positive definite symmetric matrices P, Γ, such that the following LMI is satisfied for $i = 1, \dots, r$:*

$$\Psi_i = \begin{bmatrix} N_i^T P + PN_i & * \\ T^T P N_i & \frac{\mu}{\sigma} P_1 - \frac{2}{\sigma} T^T P T \end{bmatrix} < 0, \tag{12}$$

and

$$T^T P - SC = 0, \tag{13}$$

and the fault estimation algorithm is selected as

$$\dot{\hat{f}} = \Gamma S(\dot{r}_e + \sigma r_e), \tag{14}$$

where $r_e = y - \hat{y} = y - C\hat{x}$ is a residual, then the state error and the fault error converge to zero.

Proof. The candidate Lyapunov function is selected as

$$V = e^T P e + \frac{1}{\sigma} \tilde{f}^T \Gamma^{-1} \tilde{f}. \tag{15}$$

Then, we can obtain the derivative of the Lyapunov function as

$$\begin{aligned}\dot{V} &= \dot{e}^T P e + e^T P \dot{e} + \frac{1}{\sigma}\dot{\tilde{f}}^T \Gamma^{-1} \tilde{f} + \frac{1}{\sigma}\tilde{f}^T \Gamma^{-1} \dot{\tilde{f}} \\ &= \sum_{i=1}^{r} \rho_i (e^T (N_i^T P + P N_i) e + 2\tilde{f}^T (T^T P e \\ &\quad + \frac{1}{\sigma}\Gamma^{-1}\dot{\tilde{f}})\end{aligned} \tag{16}$$

According to Eqn. (14) and the residual $r_e = Ce$, we have

$$\dot{\tilde{f}} = \dot{f} - \dot{\hat{f}} = \dot{f} - \Gamma S C(\dot{e} + \sigma e). \tag{17}$$

Substituting (17) in (16), the derivative of the Lyapunov function becomes

$$\begin{aligned}\dot{V} &= \sum_{i=1}^{r} \rho_i (e^T (N_i^T P + P N_i) e + 2\tilde{f}^T T^T P e \\ &\quad + \frac{2}{\sigma}\tilde{f}^T \Gamma^{-1}(\dot{f} - \Gamma S C(\dot{e} + \sigma e)))) \\ &= \sum_{i=1}^{r} \rho_i (e^T (N_i^T P + P N_i) e + 2\tilde{f}^T (T^T P - SC) e \\ &\quad + \frac{2}{\sigma}\tilde{f}^T \Gamma^{-1}\dot{f} - \frac{2}{\sigma}\tilde{f}^T S C N_i e - \frac{2}{\sigma}\tilde{f}^T S C T \tilde{f}).\end{aligned} \tag{18}$$

According to the assumption, we have that the derivative of fault $f(t)$ is bounded, i.e., $\|\dot{f}(t)\| < \alpha_1$, where $0 \le \alpha_1 < \infty$. Using Lemma 1, we obtain

$$\begin{aligned}&\frac{2}{\sigma}\tilde{f}^T \Gamma^{-1}\dot{f} \\ &\quad \le \frac{1}{\mu\sigma}\tilde{f}^T P_1 \tilde{f} + \frac{\mu}{\sigma}\dot{f}^T \Gamma^{-T} P_1^{-1} \Gamma^{-1}\dot{f} \\ &\quad \le \frac{1}{\mu\sigma}\tilde{f}^T P_1 \tilde{f} + \frac{\mu}{\sigma}{\alpha_1}^2 \lambda_{\max}(\Gamma^{-T} P_1^{-1} \Gamma^{-1}).\end{aligned} \tag{19}$$

Notice that if the fault is a constant, i.e., $\dot{f}(t) = 0$, the inequality (19) is not required. The fault estimation algorithm is to estimate a constant fault. In the work of Hamdi *et al.* (2012), by assuming the fault as a step, i.e., $\dot{f}(t) = 0$, a method of fault detection and isolation via a proportional integral observer has been proposed. In our method, the condition for the fault is expanded, i.e., the derivative of the fault is bounded.

Substituting (13) into (18) and using (19), we obtain

$$\begin{aligned}\dot{V} &= \sum_{i=1}^{r} \rho_i (e^T (N_i^T P + P N_i) e - \frac{2}{\sigma}\tilde{f}^T T^T P N_i e \\ &\quad + \frac{2}{\sigma}\tilde{f}^T \Gamma^{-1}\dot{f} - \frac{2}{\sigma}\tilde{f}^T T^T P T \tilde{f}) \\ &\le \sum_{i=1}^{r} \rho_i (e^T (N_i^T P + P N_i) e \\ &\quad + \frac{\mu}{\sigma}{\alpha_1}^2 \lambda_{\max}(\Gamma^{-T} P_1^{-1} \Gamma^{-1}) \\ &\quad + \frac{1}{\mu\sigma}\tilde{f}^T P_1 \tilde{f} - \frac{2}{\sigma}\tilde{f}^T T^T P N_i e \\ &\quad - \frac{2}{\sigma}\tilde{f}^T T^T P T \tilde{f}).\end{aligned} \tag{20}$$

Defining the vector $\xi = \begin{bmatrix} e & \tilde{f} \end{bmatrix}^T$, $\dot{V}$ can be written as

$$\dot{V} = \sum_{i=1}^{r} \rho_i \xi^T \Psi_i \xi + \frac{\mu}{\sigma}\alpha_1 \lambda_{\max}(\Gamma^{-T} P_1^{-1} \Gamma^{-1}), \tag{21}$$

where

$$\Psi_i = \begin{bmatrix} N_i^T P + P N_i & * \\ -\frac{1}{\sigma} T^T P N_i & \frac{1}{\mu\sigma} P_1 - \frac{2}{\sigma} T^T P T \end{bmatrix}.$$

Using Lemma 2 and Eqn. (19), if the matrix $\Psi_i < 0$ exists, we have

$$\dot{V} \le -\varepsilon \|\xi\|^2 + \frac{\mu}{\sigma}\alpha_1 \lambda_{\max}(\Gamma^{-T} P_1^{-1} \Gamma^{-1}), \tag{22}$$

where $\varepsilon = \min(\lambda_{\min}(-\Psi_i))$. Then $\dot{V} < 0$ for

$$\varepsilon \|\xi\|^2 > \frac{\mu}{\sigma}\alpha_1 \lambda_{\max}(\Gamma^{-T} P_1^{-1} \Gamma^{-1}).$$

According to the Lyapunov stability theory, both the error $e(t)$ and the fault $f(t)$ converge to a small set. ■

Now, to guarantee the stability of the LPV system is to find a suitable matrix by solving LMIs.

3.3. Active fault tolerant control for an actuator fault. In this section, an active fault tolerant control subject to an actuator fault is presented. The structure of the active tolerance control for a wind turbine system is shown in Fig. 1. The input of the baseline controller for the pitch angle and the generator torque is denoted by u_{base}, which it will be introduce in the following section. Then, for the actuator fault, the input of the fault tolerant control is

$$u_{\text{FTC}} = u_{\text{base}} + \sum_{i=1}^{r} \rho_i K_{fi} \hat{f}, \tag{23}$$

where matrix $K_{fi} = -B_i^{\dagger} F$ is supposed to compensate the actuator fault, and $B_i^{\dagger}$ is a pseudoinverse of B_i.

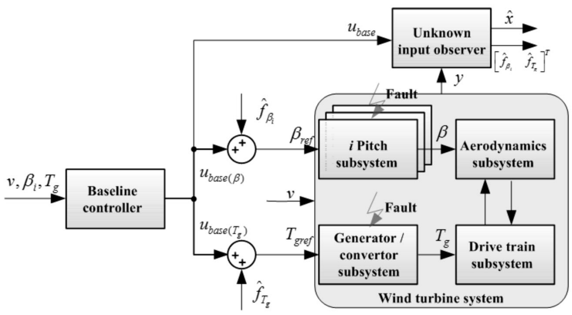

Fig. 1. Scheme of active fault tolerant control for the wind turbine system.

3.4. Steps for calculating the solution of the UIO.

In this subsection, we will introduce a method for computing the parameters of the UIO system. From the foregoing condition for the UIO (Eqn. (6)), it is rewritten as follows:

$$\begin{aligned} M &= EC + I_2, \\ MD_i &= 0. \end{aligned} \tag{24}$$

The expansion of (24) gives

$$\begin{bmatrix} M & E \end{bmatrix} \begin{bmatrix} I_2 & D_1 & \dots & D_r \\ -C & 0 & \dots & 0 \end{bmatrix} = \begin{bmatrix} I_2 & 0 & \dots & 0 \end{bmatrix}. \tag{25}$$

Define matrices

$$\begin{aligned} H &= \begin{bmatrix} M & E \end{bmatrix}, \\ Y &= \begin{bmatrix} I_2 & D_1 & \dots & D_r \\ -C & 0 & \dots & 0 \end{bmatrix}, \\ Q &= \begin{bmatrix} I_2 & 0 & \dots & 0 \end{bmatrix}. \end{aligned}$$

Y, Q are known matrices and H is an unknown matrix that needs to be solved. The condition for solvability of Eqn. (25) is that Y has full column rank (Hassanabadi *et al.*, 2016). Then it satisfies

$$\begin{aligned} \operatorname{rank}(Y) = \operatorname{rank}(I_2) + \operatorname{rank}(D_1) + \dots \\ + \operatorname{rank}(D_r). \end{aligned} \tag{26}$$

Notice that the condition ensures the solvability of Eqn. (26). The solution is given as

$$H = QY^{\dagger}, \tag{27}$$

where $Y^{\dagger}$ is a pseudoinverse of Y. If Y has full column rank, we get

$$Y^{\dagger} = (Y^T Y)^{-1} Y^T. \tag{28}$$

The matrix $Y^{\dagger}$ can be partitioned into parts H_1 and H_2 of the appropriate dimensions. Equation (27) can be rewritten as

$$H = \begin{bmatrix} M & E \end{bmatrix} = Q \begin{bmatrix} H_1 & H_2 \end{bmatrix}. \tag{29}$$

Thus, the solution of M and E is given as follows:

$$\begin{aligned} M &= QH_1, \\ E &= QH_2. \end{aligned} \tag{30}$$

Substituting (30) in (6), we obtain

$$\begin{aligned} N_i &= QH_1 A_i - K_i C, \\ L_i &= K_i(I_1 + CE) - QH_1 A_i QH_2, \\ T &= QH_1 F. \end{aligned} \tag{31}$$

Since the inequalities in Eqn. (12) are bilinear matrix ones, using Theorem 1, we can calculate the solution.

Theorem 1. *If there exists a positive definite symmetric matrix P and matrices $\bar{K}_i$, for $i = 1, \dots, r$, such that*

$$\begin{bmatrix} \Psi & * \\ -\frac{1}{\sigma} T^T PMA_i - \frac{1}{\sigma} T^T \bar{K}_i C_i & \frac{1}{\mu\sigma} P_1 - \frac{2}{\sigma} T^T PT \end{bmatrix} < 0, \tag{32}$$

where $\Psi = (MA_i)^T P + PMA_i - C^T \bar{K}_i^T - \bar{K}_i C$, then the UIO (Eqn. (5)) exists and the estimation error converges to zero.

Proof. The proof is straightforward if we make the substitutions $\bar{K}_i = PK_i$ (Eqn. (32)), according to Lemma 2. ■

Notice that by solving the LMI (32), the matrices P and $\bar{K}_i$ can be obtained. Then the remaining matrices can be calculated. The technique for designing the unknown input observer can be summarized as Algorithm 1.

Algorithm 1. Unknown input observer design.

Step 1. Compute H from Eqn. (27), and obtain the matrices M, E.

Step 2. Solve the LMI from the inequalities (32) and obtain the matrices P, Then calculate $K_i = P^{-1}\bar{K}_i$ and $S = T^T PC^{\dagger}$.

Step 3. Calculate the matrices G_i from Eqn. (6).

Step 4. Calculate the matrices N_i, L_i, T from Eqn. (31).

4. Wind turbine system description

Usually, a typical wind turbine system consists mainly of an aerodynamic subsystem, a drive train subsystem, a pitch subsystem and a generator subsystem. A benchmark wind turbine system model is described by Odgaard *et al.* (2009) and Simani *et al.* (2013). The benchmark model can deal with system level faults in different subsystems. The purpose of the benchmark model is to test and evaluate different kinds of fault detection and accommodation schemes on a realistic wind turbine system.

4.1. Aerodynamic subsystem. The aerodynamics of the wind turbine system are modeled as a torque $T_a(t)$ acting on the rotor blades. For three blades with small differences between the values of β_i, where $i = 1, 2, 3$, the torque can be given as

$$T_a(t) = \frac{1}{6\lambda}\sum_{i=1}^{3}\rho\pi R^3 v^2 C_p(\lambda, \beta_i), \tag{33}$$

where C_p is the power coefficient, v is the wind speed, R is the rotor-plane radius, λ is the tip speed ratio, ρ is the air density, β is the pitch angle. If the pitch angles are equal, the aerodynamic torque can be rewritten as

$$T_a(t) = \frac{1}{2\lambda}\rho\pi R^3 v^2 C_p(\lambda, \beta). \tag{34}$$

4.2. Drive train subsystem. For the gearbox in the wind turbine system, a two-mass drive train model can be obtained as

$$\begin{cases} \dot{\theta}(t) = \omega_r - \dfrac{\omega_g}{n_g}, \\ J_t\dot{\omega}_r(t) = T_a - K_s\theta - B_s\omega_r + B_s\omega_g, \\ J_g\dot{\omega}_g(t) = \dfrac{1}{n_g}(K_s\theta + B_s\omega_r - B_s\omega_g) - T_g, \end{cases} \tag{35}$$

where n_g is the gearbox ratio, K_s and B_s are the stiffness and the damping coefficient, respectively. J_t and J_g are respectively the inertia of the rotor and the generator, θ is the torsion angle of the drive train and ω_g is the generator speed.

4.3. Generator and converter subsystem. The generator and the converter can be simplified as a first order system and given as

$$\dot{T}_g(t) = -\frac{T_g}{\tau_1} + \frac{T_{g,\mathrm{ref}}}{\tau_1}, \tag{36}$$

where $T_{g,\mathrm{ref}}$ is the reference generator torque signal and τ_1 is the time parameter of the electrical subsystem. The potential fault in this system caused by the converter fault may result in an actuator offset.

4.4. Pitch subsystem. According to Shi and Patton (2015) or Odgaard *et al.* (2009), the hydraulic pitch subsystem is modeled as a second order system with reference pitch angle β_{ref},

$$\ddot{\beta} = -2\zeta\omega_n\dot{\beta} - \omega_n^2\beta + \omega_n^2\beta_{\mathrm{ref}}, \tag{37}$$

where ω_n, ζ are the natural frequency and damping ratio parameters, respectively. In the work of Shi and Patton (2015), the increased air content or the drop of oil pressure will change the dynamics of the pitch system and cause an actuator failure.

Having defined the fault effectiveness parameter θ_f, $\theta_f \in [0, 1]$, the parameters of the pitch system become $\omega_n = \omega_{nf}, \zeta = \zeta_f$ correspond to a full fault on the actuator with $\theta_f = 1$ and $\omega_n = \omega_{n0}, \zeta = \zeta_0$ correspond to a fault-free on the actuator with $\theta_f = 0$. The parameters of the pitch system can be rewritten as with the actuator fault:

$$\begin{aligned} \omega_n^2 &= (1-\theta_f)\omega_{n0}^2 + \theta_f\omega_{nf}^2, \\ \zeta\omega_n &= (1-\theta_f)\zeta_0\omega_{n0} + \theta_f\zeta_f\omega_{nf}, \end{aligned} \tag{38}$$

If the pitch angle β is treated as an output and $x_\beta = \begin{bmatrix}\beta & \dot{\beta}\end{bmatrix}^T$ is treated as a state variable, the model of the pitch system can be rewritten in state space form as

$$\begin{aligned} \dot{x}_\beta = &\begin{bmatrix} 0 & 1 \\ -\omega_{n0}^2 & -2\zeta_{n0}\omega_{n0} \end{bmatrix} x_\beta \\ &+ \begin{bmatrix} 0 \\ \omega_{n0}^2 \end{bmatrix}\beta_{\mathrm{ref}} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} f_\beta, \end{aligned} \tag{39}$$

where

$$\begin{aligned} f_\beta = &((\omega_{nf}^2 - \omega_{n0}^2)\beta + 2(\zeta_{nf}\omega_{nf} - \zeta_{n0}\omega_{n0})\dot{\beta} \\ &+ (\omega_{nf}^2 - \omega_{n0}^2)\beta_{\mathrm{ref}})\theta_f \end{aligned}$$

is the pitch actuator fault. Remark that dropped main line pressure or high air content in oil yield changes in the parameter of the hydraulic pitch system and cause a failure in the pitch actuator. The faults considered only change the parameters and do not change the model structure. The other faults, such as sensor faults, etc., are not discussed in this study.

4.5. Baseline control for the wind turbine system. In this subsection, a baseline control strategy for the power will be introduced. With the power of the wind turbine increasing, the system is usually designed to work in different regions. According to the wind speed, it can be divided into two main regions: a high speed region (HSR) and a low speed region (LSR). In the HSR, the main objective is to maintain the output power within the rating value by adjusting the pitch angle, while in the LSR the objective is to track the optimal power by changing the generator torque. Therefore, the reference signals for the controller in the different regions are

$$\begin{aligned} \beta_{\mathrm{ref}}(t) &= \begin{cases} 0 & \text{for LSR}, \\ \beta_{\text{non-zero}} & \text{for HSR}, \end{cases} \\ T_{g,\mathrm{ref}}(t) &= \begin{cases} T_{g,\mathrm{opt}} & \text{for LSR}, \\ T_{g,\mathrm{rat}} & \text{for HSR}, \end{cases} \end{aligned} \tag{40}$$

where $\beta_{\text{non-zero}}$ is obtained by using the classical proportional-integral (PI) controller, $T_{g,\mathrm{rat}}$ is the rating torque corresponding to the rating power, $T_{g,\mathrm{opt}}$ is the

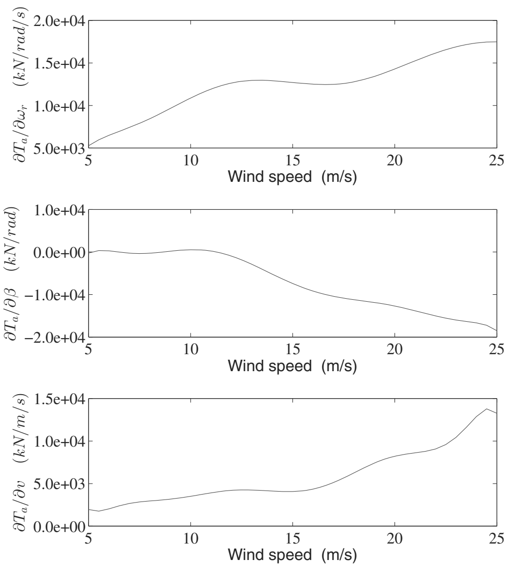

Fig. 2. Partial derivatives of aerodynamic torque T_a.

optimal torque which can be calculated by the wind speed and the tip speed ratio. The PI controller is given as

$$u_{\text{base}}(t) = k_p\Big(e(t) + 1/T_i \int e(t)\,\mathrm{d}t\Big), \qquad (41)$$

where k_p, T_i are the parameters of the PI controller. The switching rules in the different regions are given by Odgaard *et al.* (2009).

Since the aerodynamic torque can be usually approximately equivalent to a nonlinear function (cf. Bianchi and De Battista, 2007), it can be linearized as follows:

$$T_a(\varpi) = B_r(\varpi)\omega_r + k_{rb}(\varpi)\beta + k_{rv}(\varpi)v, \qquad (42)$$

where $\varpi = (v, \omega_r, \beta)$ and

$$\begin{aligned} B_r(\varpi) &= \frac{\partial T_a}{\partial \omega_r}\Big|_{\varpi} = \frac{T_a}{\bar{\omega}_r}\frac{\partial C_q/\partial\lambda}{C_q/\lambda}\Big|_{\varpi}, \\ k_{rv}(\varpi) &= \frac{\partial T_a}{\partial v}\Big|_{\varpi} = \frac{T_a}{\bar{v}}\Big(2 - \frac{\partial C_q/\partial\lambda}{C_q/\lambda}\Big|_{\varpi}\Big), \\ k_{rb}(\varpi) &= \frac{\partial T_a}{\partial \beta}\Big|_{\varpi} = \frac{T_a}{\bar{\beta}}\frac{\partial C_q/\partial\beta}{C_q/\lambda}\Big|_{\varpi}. \end{aligned} \qquad (43)$$

This can be evaluated at the equilibrium point ϖ along the normal operating trajectory. If the wind turbine is operating in the nominal region (Bianchi *et al.*, 2007), the variables β and ω_r at the equilibrium point ϖ can be described uniquely by the wind speed, i.e., $\varpi = v$. Figure 2 shows the partial derivatives of the aerodynamic torque. Thus, defining the state vector,

$$x = [\theta \quad \omega_r \quad \omega_g \quad T_g \quad \beta_1 \quad \dot{\beta}_1 \quad \beta_2 \quad \dot{\beta}_2 \quad \beta_3 \quad \dot{\beta}_3]^T,$$

the LPV model of the wind turbine system can be parameterized by the wind speed and is given by

$$\begin{aligned} \dot{x}(t) &= A(v)x(t) + Bu(t) + D(v)v, \\ y(t) &= Cx(t), \end{aligned} \qquad (44)$$

where

$$A(v) = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix},$$

$$A_{11} = \begin{bmatrix} 0 & 1 & -1/n_g & 0 \\ -\frac{K_s}{J_t} & -\frac{(B_s+B_r(v))}{J_t} & \frac{B_s}{n_g J_t} & \frac{k_{rb}(v)}{J_t} \\ \frac{K_s}{n_g J_g} & \frac{B_s}{n_g J_g} & -\frac{(B_s/n_g^2+B_g)}{J_g} & 0 \\ 0 & 0 & 0 & -\frac{1}{\tau_1} \end{bmatrix},$$

$$A_{12} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{K_{rb}}{3J_t} & 0 & \frac{K_{rb}(v)}{3J_t} & 0 & \frac{K_{rb}(v)}{3J_t} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$A_{21} = [\mathbf{0}]_{6\times 4},$$

$$A_{22} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ -\omega_n^2 & 2\zeta_n\omega_n & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & -\omega_n^2 & 2\zeta_n\omega_n & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & -\omega_n^2 & 2\zeta_n\omega_n \end{bmatrix},$$

$$B = \begin{bmatrix} 0 & 0 & 0 & \frac{1}{\tau_1} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \omega_{1,\text{ref}}^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \omega_{2,\text{ref}}^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \omega_{3,\text{ref}}^2 \end{bmatrix}^T,$$

$$C = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix},$$

$$D(v) = \begin{bmatrix} 0 & \frac{k_{rv}(v)}{J_t} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}^T.$$

Since during normal operation the wind speed varies within a certain range (i.e., $v \in [v_{\min}, v_{\max}]$) and

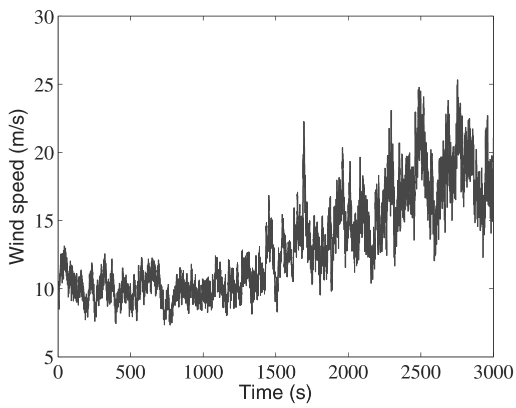

Fig. 3. Wind speed.

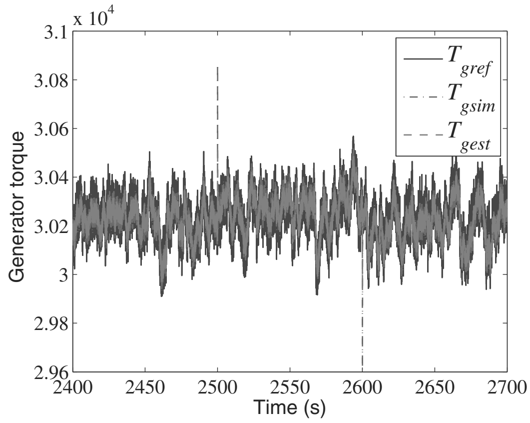

Fig. 5. Generator torque and the corresponding estimate.

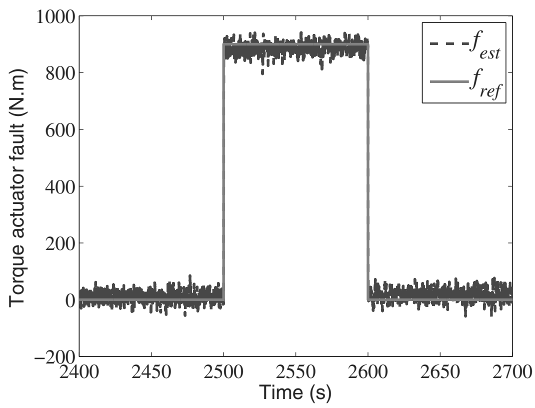

Fig. 4. Generator torque fault and its estimate.

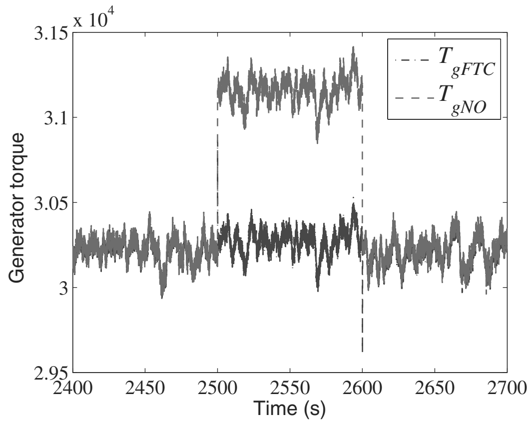

Fig. 6. Generator torque with and without FTC.

is the only variable in the LPV model, the polytopic representation of the LPV model of wind turbine system has two subsystems. According to the range of the wind speed, the weight of the subsystem can be calculated as

$$\begin{aligned} \rho_1(v) &= \frac{v_{\max} - v}{v_{\max} - v_{\min}}, \\ \rho_2(v) &= \frac{v - v_{\min}}{v_{\max} - v_{\min}}, \end{aligned} \tag{45}$$

In the wind turbine system, the pitch subsystem starts to work only if the wind speed is up to a rating value. When the wind speed is over a cut-off wind speed, the pitch subsystem will stop working. In this paper, the variation range in the wind speed is chosen from $(6, 25)$.

5. Simulation and results

In this paper, the proposed approach is tested in the Matlab/Simulink environment with a benchmark model. The detailed the parameters of wind turbine system are given after Odgaard *et al.* (2009), and the main parameters of wind turbine system are $R = 57.5$, $n_g = 95$, $J_t = 55\times10^6\,\text{kg}\cdot\text{m}^2$ $J_g = 390\,\text{kg}\cdot\text{m}^2$, $K_s = 2.7\times10^9$ Nm/rad, $B_s = 9.45$ Nm/(rad/s), $\omega_n = 11.11$, $\zeta_n = 0.6$, $\tau_1 = 0.1$.

Using the Matlab/Yalmip toolbox (Lofberg, 2004) to solve the LMIs, the matrices of the UIO can be obtained; see Eqns. (46)–(51).

The baseline controller is given after Odgaard *et al.* (2009). The parameters of the controller for the pitch angle are $k_p = 4, T_i = 4$. In the simulation, a random wind speed is selected and shown in Fig. 3.

In the following, two cases are considered to verify the proposed approach.

5.1. Generator and converter subsystem with an actuator fault.

An offset in the internal converter control loops, results in an offset in the torque input. The generator and converter subsystem fault occurred in the period from 2500 to 2600 s. In the torque fault situation, the value of the torque input is offsetting with 900 Nm. The estimated fault of the torque is illustrated in Fig. 4. The estimate tends to the reference rapidly. Since the torque fault is a constant, it indicates that the proposed method performs well with constant faults. The generator torque and its estimated value are shown in Figs. 5 and 6. Comparing the results, we see that the performance of the fault estimation algorithm is proved.

$$N_1 = \begin{bmatrix} 0 & 1.0 & -0.01053 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -49.09 & -0.000007 & 0.000000 & 0.000001 & 0.000098 & 0 & 0.000098 & 0 & 0.000098 & 0 \\ 70699.0 & 0.0203 & -0.1136 & 0.0001218 & 0.005775 & -0.000000 & 0.005775 & 0 & 0.005775 & 0 \\ 0 & 0 & 0 & -5.155 & -0.000000 & -0.000000 & -0.000000 & 0 & -0.000000 & 0 \\ 0 & 0 & 0 & 0.000000 & -52.57 & 0.5 & -0.000017 & 0 & -0.000017 & 0 \\ 0 & 0 & 0 & -0.000001 & 1088.0 & -13.33 & 0.000439 & 0 & 0.000439 & 0 \\ 0 & 0 & 0 & 0.000000 & -0.000017 & 0 & -52.57 & 0.5 & -0.000017 & 0 \\ 0 & 0 & 0 & -0.0000006 & 0.000439 & 0 & 1088.0 & -13.33 & 0.000439 & 0 \\ 0 & 0 & 0 & 0.000000 & -0.000017 & 0 & -0.000017 & 0 & -52.57 & 0.5 \\ 0 & 0 & 0 & -0.000001 & 0.000439 & 0 & 0.000439 & 0 & 1088.0 & -13.33 \end{bmatrix}, \tag{46}$$

5.2. Pitch subsystem with an actuator fault. The pitch actuator fault caused by the high air content in oil or dropped main line pressure results in changed dynamics. This type of fault is possible in all three blades. In this paper, the second and third pitch subsystems are selected as a case for the pitch actuator fault. The effectiveness parameter θ_f of the second pitch subsystem is set as 1. In the period from 2700 to 2800 s. The actuator fault of the third pitch subsystem is taken as

$$f_{\beta_3}(t) = \begin{cases} 4\sin(0.2t) + 5, & 2900 \le t \le 3000, \\ 0, & \text{otherwise.} \end{cases} \tag{52}$$

The simulation results are illustrated as follows. Figures 7 and 8 show the reference and the estimated values of faults. Figures 9 and 11 display the simulated and estimated values of the pitch angle. Figures 10 and 12 show the result of the pitch angle with and without FTC. From the fault estimation of the third pitch angle, we can see that an error appears in the estimation of the pitch fault. This illustrates that, for a fault with a bounded derivative, the proposed method can estimate the fault with a small error. From these figures, we can see that the estimation faults slightly change within the scope of the simulation value after the faults occur. The estimation algorithm for both the faults and states is efficient.

6. Conclusions

In the paper, an active fault tolerant control for a wind turbine system with an actuator fault was proposed. First, using linearization, a benchmark model of the wind turbine system was converted into LPV form. Considering both a disturbance and an actuator fault in the system, an unknown input observer based on the LPV model and an actuator fault estimation algorithm were designed. We analyzed the convergence of the observer using Lyapunov stability theory. In order to verify the proposed method, a wind turbine system with actuator faults, a torque actuator and a pitch actuator, was tested in a benchmark model. From the results, we have that both fault and state estimation algorithms perform well. The proposed fault tolerance control method is efficient, especially for an actuator fault with an offset.

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$$N_2 = \left[\begin{array}{ccccc} 0 & 1.0 & -0.01053 & 0 & 0 \\ -49.09 & -0.000236 & 0.000000 & 0.000001 & 0.000009 \\ 70699.0 & 0.0203 & -0.1136 & 0.0001218 & 0.005775 \\ 0 & 0 & 0 & -5.155 & -0.000000 \\ 0 & 0 & 0 & 0.000000 & -52.57 \\ 0 & 0 & 0 & -0.000001 & 1088.0 \\ 0 & 0 & 0 & 0.000000 & -0.000017 \\ 0 & 0 & 0 & -0.000001 & 0.000439 \\ 0 & 0 & 0 & 0.000000 & -0.000017 \\ 0 & 0 & 0 & -0.000001 & 0.0004386 \end{array} \right.$$

$$\left. \begin{array}{ccccc} 0 & 0 & 0 & 0 & 0 \\ 0 & 0.000009 & 0 & 0.000009 & 0 \\ -0.000000 & 0.005775 & 0 & 0.005775 & 0 \\ -0.000000 & -0.000000 & 0 & -0.000000 & 0 \\ 0.5 & -0.000017 & 0 & -0.000017 & 0 \\ -13.33 & 0.000439 & 0 & 0.000439 & 0 \\ 0 & -52.57 & 0.5 & -0.000017 & 0 \\ 0 & 1088.0 & -13.33 & 0.000439 & 0 \\ 0 & -0.000017 & 0 & -52.57 & 0.5 \\ 0 & 0.000439 & 0 & 1088.0 & -13.33 \end{array} \right], \tag{47}$$

$$L_1 = \left[\begin{array}{cccc} -0.000000 & -0.000000 & -0.000000 & -0.000000 \\ -0.000001 & -0.000074 & -0.000074 & -0.000074 \\ -0.002625 & -0.002888 & -0.002888 & -0.002888 \\ 0.07754 & 0.000000 & 0.000000 & 0.000000 \\ -0.000000 & 26.29 & 0.000008 & 0.000008 \\ 0.000000 & -667.3 & -0.000219 & -0.000219 \\ -0.000000 & 0.000008 & 26.29 & 0.000008 \\ 0.000000 & -0.000219 & -667.3 & -0.000219 \\ -0.000000 & 0.000008 & 0.000008 & 26.29 \\ 0.000000 & -0.000219 & -0.000219 & -667.3 \end{array} \right], \tag{48}$$

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$$L_2 = \begin{bmatrix} -0.000000 & -0.000000 & -0.000000 & -0.000000 \\ -0.000001 & -0.000119 & -0.000119 & -0.000119 \\ -0.002625 & -0.002888 & -0.002888 & -0.002888 \\ 0.07754 & 0.000000 & 0.000000 & 0.000000 \\ -0.000000 & 26.29 & 0.000008 & 0.000008 \\ 0.000000 & -667.3 & -0.000219 & -0.000219 \\ -0.000000 & 0.000008 & 26.29 & 0.000008 \\ 0.000000 & -0.000219 & -667.3 & -0.000219 \\ -0.000000 & 0.000008 & 0.000008 & 26.29 \\ 0.000000 & -0.000219 & -0.000219 & -667.3 \end{bmatrix}, \tag{49}$$

$$E = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ -0.0000 & 0.0000 & 0 & 0 \\ -0.5000 & 0.0000 & 0 & 0 \\ 0 & -0.50000 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & -0.5000 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -0.5000 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \tag{50}$$

$$G_1 = G_2 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0.0000 & 0 & 0 & 0 \\ 2.5000 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 123.4321 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 123.4321 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 123.4321 \end{bmatrix} = T. \tag{51}$$

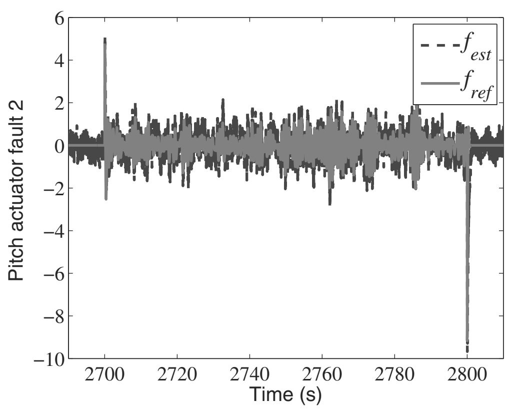

Fig. 7. Second pitch angle fault and its estimate.

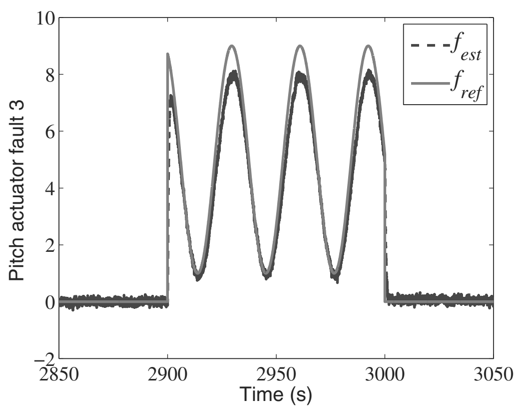

Fig. 8. Third pitch angle fault and its estimate.

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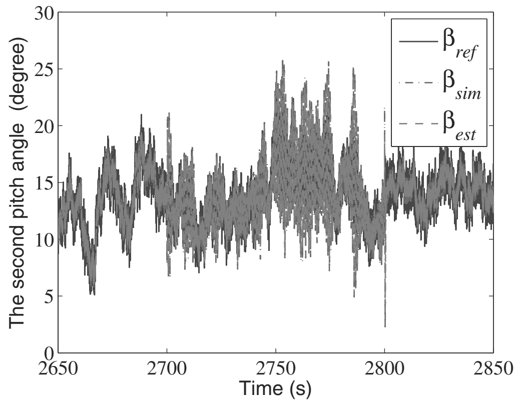

Fig. 9. Second pitch angle and its estimate.

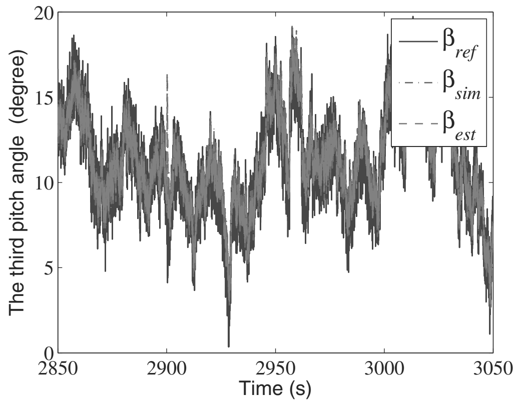

Fig. 11. Third pitch angle and its estimate.

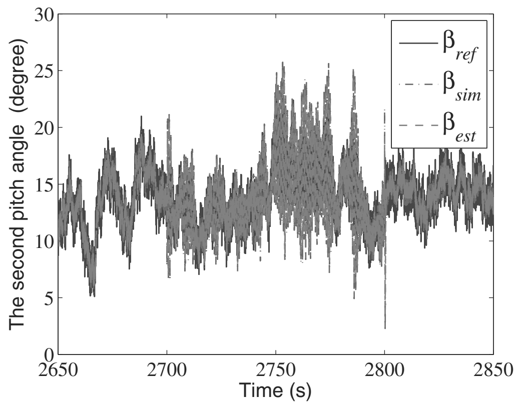

Fig. 10. Second pitch angle with and without FTC.

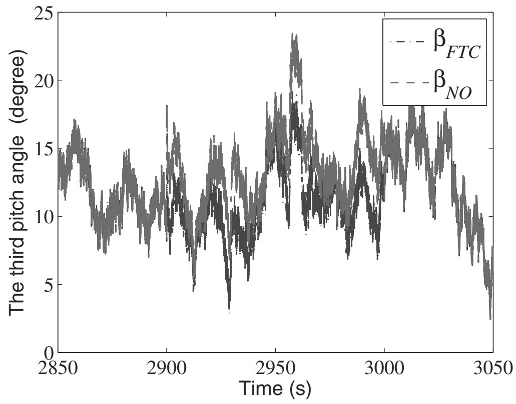

Fig. 12. Third pitch angle with and without FTC.

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Appendix

Table A1. Nomenclature.

Parameter	Description
v	wind speed
C_p	power coefficient
τ_1	time constant
λ	tip speed ratio
β_i	i-th pitch angle
ω_r, ω_g	rotor, generator speeds
ω_n, ζ_n	natural frequency, damping ratio
T_a, T_g	aerodynamics, generator torques
J_t, J_g	rotor, generator inertias
K_s, B_s	stiffness, damping coefficients
d, f	disturbance, fault vectors
D_i, F	disturbance, fault matrices
A_i, B_i, C_i	system matrices
N_i, G_i, L_i, T, E	observer gains
$\hat{x}$	estimate of x
$\tilde{x}$	result of $\tilde{x} = x - \hat{x}$
$x^\dagger$	pseudoinverse of x
$\dot{x}$	derivative of x

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