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IFAC PapersOnLine 51-24 (2018) 1141–1148

Banks of estimators and decision mechanisms for pitch actuator and sensor FE in wind turbines ⋆

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Abstract: Wind turbines are prone to multiple different faults and input observability conditions are not always guaranteed for these faults. In such cases, it is not possible to build estimators which provide appropriate fault estimates for its further use in active FTC schemes such as fault tolerant MPC. Provided that these faults are generally non-simultaneous, we make use of this property for building banks of model-based estimators and statistical-based decision mechanisms that provide appropriate fault estimates for enhancing active FTC capabilities. We apply these strategies to a well-known wind turbine FDI and FTC benchmark and we show the effectiveness of the bank of estimators and decision mechanisms for estimating the faults occurring in the pitch system of a wind turbine.

Keywords: Fault estimation, fault accommodation, wind turbines.

1. INTRODUCTION

Reliability and maintainability of wind turbines emerges as a key issue in wind power development (Cheng and Zhu (2014)). Then, fault detection and isolation (FDI) and fault tolerant control (FTC) of wind turbines have received much attention in the last decade. The two main tasks in FDI are fault detection, which consists on determining whether a fault has occurred, and fault isolation, which is devoted to find the location of the faults. Most FDI schemes are based on residual generation approaches using the so-called residuals (Chen and Patton (2012)). Regarding FTC, there exist two main approaches: passive and active FTC (Patton (2015)). In passive FTC (PFTC), controllers are fixed and designed to be robust against a class of presumed faults and, thus, PFTC has limited fault-tolerant capabilities. For its part, active FTC (AFTC) reacts to faults by reconfiguring control actions so that the stability and acceptable performance of the entire system can be maintained. Inside AFTC, Blanke et al. (2006) and Patton (2015) distinguish between system reconfiguration (SR) and fault accommodation (FA). The difference between them is that SR uses different input-output relations between the controller and the system when the fault is present in the system while FA does not change these relations. Unlike PFTC, AFTC requires FDI. However, the use of the residuals provided by FDI schemes in FA implies intrinsic difficulties due to the complexity derived from the reconstruction of faults from residuals (Zhang and Jiang (2008)). As claimed in Zhang et al. (2012), fault estimation (FE), which aims to identify the magnitude of the faults, appears as a bridge between FDI and FA (see Lan and Patton (2016) and Han et al. (2016)). Advanced observer techniques such as proportional and integral (PI) observers are usually utilized for FE (Gao et al. (2015)).

A well-known benchmark for FDI and FTC of wind turbines was developed in Odgaard et al. (2013). The benchmark takes account on a wide variety of faults to which the wind turbine is prone: it contains actuator, sensor and components fault. A vast variety of residuals-based solutions have been presented for this FDI problem, see Odgaard and Stoustrup (2012). Regarding FTC, both PFTC and AFTC strategies have been applied to wind turbines in Sloth et al. (2011) and Blesa et al. (2014). In Lan et al. (2016) and Simani and Castaldi (2014), AFTC strategies based on FE are applied to these systems. However, all these works assume that the pitch system of the wind turbine is only prone to actuator faults and, thus, the pitch sensor faults are not taken into account. The same assumption is considered in the FE solution presented in Witczak et al. (2017).

One of the main problems in the use of common FE techniques for AFTC arises when the faults affecting the system do not verify the input observability conditions detailed in Hou and Patton (1998). A solution to cope with this problem in a residual-based FDI context is the use of generalized observers (Chen and Patton (2012)); however, this issue becomes more challenging in the FE framework.

The main objective of this work is to present a FE strategy for the actuator and sensor faults occurring in the pitch system of a wind turbine. These faults do not verify input observability conditions and we propose an FE structure based on a bank of PI observers. Each observer estimates a subset of faults inputs and the bank, together with

⋆ This work has been supported by grant FPU14/01592 from MECD and by projects P11B2015-42 from Universitat Jaume I de Castelló and MINECO project number TEC2015-69155-R.

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2018.09.715

appropriate decision mechanisms, provides fault estimates for feeding any FA scheme.

The outline of this work is as follows. First, we state the problem in Section 2. In Section 3, we present a bank of subsets of observable fault inputs and in Section 4, we explain the proposed FE strategy. Finally, Section 5 presents the simulation results of applying the proposed scheme to the pitch system of the wind turbines. Section 6 summarizes the main conclusions.

Notation: Let A and B be some matrix and a be some vector. $A[i,j]$ denotes the element in the i-th row and j-th column of A and $a[i]$ denotes the i-th element in a. Vector $x(t)$ denotes a stochastic process at time t. Expected value and probability are denoted by $\mathbb{E}\{\}$ and $\mathbb{P}\{\}$. I_n is the identity matrix of size $n \times n$, $\mathbf{1}_n$ is a column vector of ones and length n and $\mathbf{0}_n$ is a column vector of zeros and length n. The direct sum is denoted by $\oplus$ ans $\#S$ refers to the cardinality of a set S.

2. PROBLEM STATEMENT

The benchmark in Odgaard et al. (2013) describes a three-bladed wind turbine which consists of four main systems: the drive train, the generator and converter, the blade and pitch and the controller. In this work, we deal with the faults affecting the pitch systems of the wind turbine.

Each hydraulic pitch system p (with $p = 1, 2, 3$) is a second order closed-loop system between the reference angle provided by the collective pitch controller, β_r, and the averaged measurement of the pitch angle, $\beta_{m,p}$, provided by two redundant sensors, $\beta_{m(1),p}$ and $\beta_{m(2),p}$. Both sensors entail zero-mean Gaussian measurement noises ($v_{m(1),p}$ and $v_{m(2),p}$) of known standard deviation σ_v that disturb the closed loop. Then, we model these disturbances as additive signals that affect altogether the measurements and the reference. Similar applies to sensor faults, which we denote as $f_{m(1),p}$ and $f_{m(2),p}$ (see Fig.1). Both sensor measurements are used in the closed-loop so as to average the effect of these faults. The pitch actuator may suffer from dynamical changes due to pressure drops and the closed-loop parameters of the pitch system can be represented as convex combinations of their values at fault-free and low pressure scenarios (Shi and Patton (2015); Lan et al. (2016)):

$$\omega_{n,p}^2(t) = w_{n_0}^2 + (\omega_{n_f}^2 - \omega_{n_0}^2)\, f_p(t),$$
$$\xi_p(t)\, \omega_{n,p}(t) = \xi_0\, \omega_{n_0} + (\xi_f\, \omega_{n_f} - \xi_0\, \omega_{n_0}^2\,) f_p(t),$$

where ω_{n_0} and ξ_0 are the nominal parameters of the close loop and ω_{n_f} and ξ_f describe the faulty behaviour. The function $f_p \in [0,1]$ is a fault indicator so that $f_p = 0$ and $f_p = 1$ correspond, respectively, to normal and faulty operation. In all, the transfer matrix between the inputs and the outputs of the system satisfies

$$\begin{bmatrix}\beta_{m(1),p}\\ \beta_{m(2),p}\end{bmatrix} = \begin{bmatrix} G_0 & G_0 \\ 1-G_0/2 & -G_0/2 \\ -G_0/2 & 1-G_0/2 \\ G_0/\omega_{n_0}^2 & G_0/\omega_{n_0}^2 \\ 1-G_0/2 & -G_0/2 \\ -G_0/2 & 1-G_0/2 \end{bmatrix}^T \begin{bmatrix}\beta_r \\ f_{m(1),p} \\ f_{m(2),p} \\ f_{a,p} \\ v_{m(1),p} \\ v_{m(2),p}\end{bmatrix} \qquad (1)$$

(where we have omitted the dependence on s), with

Table 1. Pitch parameters in the benchmark.

	Parameter	Value
ξ_0	Nominal damping factor	0.6
w_{n_0}	Nominal natural frequency	11.11 rad/s
ξ_f	Faulty damping factor	0.9
w_{n_f}	Faulty natural frequency	3.42 rad/s
σ_v^2	Measurement noise variance	0.2°

$$G_0(s) = \frac{\omega_{n_0}^2}{s^2 + 2\,\xi_0\,\omega_{n_0}\, s + \omega_{n_0}^2}$$

being the close-loop transfer function and $f_{a,p}$ being an additive signal defined as

$$f_{a,p}(t) = \Big((\omega_{n_f}^2 - \omega_{n_0}^2)\,(\beta_{r,p}(t) - \beta_p(t)) - 2\,(\xi_f\,\omega_{n_f} - \xi_0\,\omega_{n_0})\,\dot\beta_p(t)\Big) f_p(t), \qquad (2)$$

which takes account on process faults and it can be used in fault accommodation. A minimal realization of (1) is

$$\dot x(t) = A\,x(t) + B\,u(t) + E\,f(t) + G\,v(t), \qquad (3a)$$
$$y(t) = C\,x(t) + F\,f(t) + H\,v(t), \qquad (3b)$$

with $x(t) \in \mathbb{R}^{n_x}$ being the state vector, $u(t) \in \mathbb{R}^{n_u}$ being the input vector, $y(t) \in \mathbb{R}^{n_y}$ being the output vector, $f(t) \in \mathbb{R}^{n_f}$ being the fault vector and $v(t) \in \mathbb{R}^{n_v}$ being the noise vector defined as

$$x = \begin{bmatrix}\beta_p \\ \dot\beta_p\end{bmatrix}, u = \beta_r, y = \begin{bmatrix}\beta_{m(1),p}\\ \beta_{m(2),p}\end{bmatrix}, f = \begin{bmatrix} f_{m(1),p} \\ f_{m(2),p} \\ f_{a,p}\end{bmatrix}, v = \begin{bmatrix} v_{m(1),p} \\ v_{m(2),p}\end{bmatrix}.$$

The state-space matrices are given by

$$A = \begin{bmatrix} 0 & 1 \\ -w_{n_0}^2 & -2\,\xi_0\,w_{n_0}\end{bmatrix}, \; B = \begin{bmatrix} 0 \\ w_{n_0}^2\end{bmatrix},$$
$$E = \begin{bmatrix} 0 & 0 & 0 \\ -w_{n_0}^2/2 & -w_{n_0}^2/2 & 1\end{bmatrix}, \; G = \begin{bmatrix} 0 & 0 \\ -w_{n_0}^2/2 & -w_{n_0}^2/2\end{bmatrix},$$
$$C = [\mathbf{1}_2 \;\; \mathbf{0}_2]\,, \; F = [I_2 \;\; \mathbf{0}_2]\,, \; H = I.$$

Henceforth, we shall omit the dependence on the time t. The benchmark parameter values, which are used in this paper, are detailed in Table 1. Note that the following statements are verified: **(1)** The realization (A, B, C) verifies rank $\{\mathscr{C}(A,B)\} = n_x$ and rank $\{\mathscr{O}(A,C)\} = n_x$, where $\mathscr{C}(\cdot)$ denotes the controllability matrix and $\mathscr{O}(\cdot)$ denotes the observability matrix. **(2)** The noises are Gaussian, zero-mean and of known covariance $\mathbb{E}\{v\,v^T\} = V = \sigma_v^2 \oplus \sigma_v^2$. **(3)** The fault signal is zero at fault-free scenarios and takes non-zero values from the moment of the fault appearance.

The objective of this work is to achieve FE so as to use the estimate of the fault vector f in a FA scheme. For this aim, we propose to use a PI observer, which, as stated in Gao et al. (2015), is an advanced observer technique which is in an advantage position for reconstructing slow-varying additive faults.

Provided the observability of the pair (A, C), a necessary and sufficient condition for the construction of a PI observer is (Jiang et al. (2000)):

$$\text{rank}\begin{bmatrix} A & E \\ C & F\end{bmatrix} = n_x + n_f. \qquad (4)$$

This condition is directly related to the condition of input (fault) observability detailed in Hou and Patton (1998).

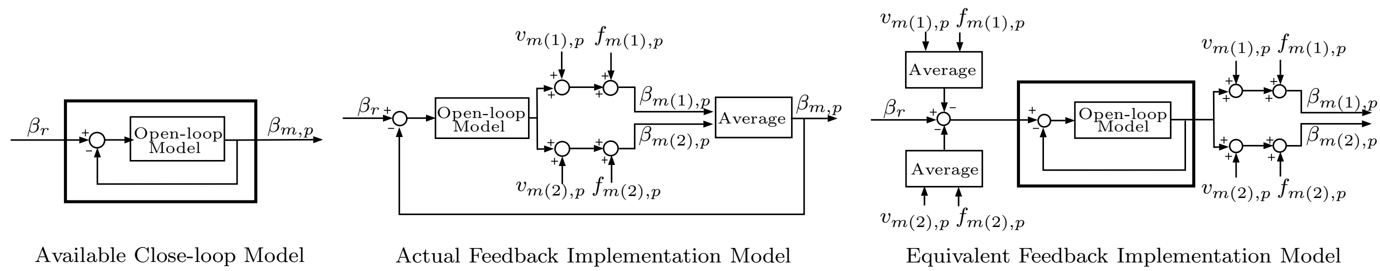

Fig. 1. Architecture of the pitch system without actuator fault.

Remark 1. When using a PI observer, we assume that f is continuously smooth with bounded first time derivative. It may be interesting to use a Proportional Multiple Integral (PMI) observer by considering the faults to be in the more general form of a polynomial over the time t with bounded d-th time derivative (Gao and Ding (2007); Koenig (2005)), especially when it comes to the actuator fault (2). Note that the existence conditions of a PMI are the same as the existence conditions of a PI in (4) (Jiang et al. (2000)). Thus, it is straightforward to extend the results presented in this work to the use of PMI observers.

The system (3) does not verify condition (4). In this paper, we propose an structure based on a bank of PI observers. Each observer estimates a subset of faults or a subset of observable inputs related to a subset of faults. This bank, together with appropriate decision mechanisms, provides fault estimates for feeding any AFTC scheme.

3. BANK OF SUBSETS OF OBSERVABLE FAULT INPUTS

3.1 Bank of Subsets of Faults in Systems with Limited Measurements

Note that the inequality

$$\operatorname{rank}\begin{bmatrix} A & E \\ C & F \end{bmatrix} \leq n_x + n_y,$$

holds for every system in the form of (3). Thus, whenever $n_f > n_y$, condition (4) cannot be verified. In such cases, we propose to define a bank of n_b different subsets of faults of size $n_s = n_y$ in such a way that every fault in f is considered, at least, by one subset in the bank. If we denote the set of the faults in vector f as $S = \{f[1], \ldots, f[n_f]\}$ and the set of the corresponding ordered indices as $\pi = \{1, \ldots, n_f\}$ (i.e., $\pi[i] = i$), each subset $S^b \subset S$ with $b = 1, \ldots, n_b$ considers $n_s < n_f$ faults (with ordered indices $\pi^b \subset \pi$), which we stack in f^b (verifying $f^b[l] = f[\pi^b[l]]$ with $l = 1, \ldots, n_s$). Similarly, for each b, we define the subset $S^{\backslash b} \subset S$ of $n_f - n_s$ faults (with ordered indices $\pi^{\backslash b} \subset \pi$) which are not taken account by the b-th subset, i.e., $S^b \cup S^{\backslash b} = S$ and $S^b \cap S^{\backslash b} = \emptyset$. We denote the vector that stacks the faults in $S^{\backslash b}$ as $f^{\backslash b}$. Provided that $S^b \neq S^c$ and $S = \cup_{b=1}^{n_b} S^b$, the number of subsets S^b verifies

$$n_b = \mathbf{C}_{n_s}^{n_f} = n_f!/n_s!/(n_f - n_s)!.$$

Let us define E^b and F^b as the matrices that stack the columns of E and F indexed by π^b (similar applies to $E^{\backslash b}$ and $F^{\backslash b}$ w.r.t. $\pi^{\backslash b}$). Now, in order to build a PI observer for certain subset of faults S^b, the following condition must be verified

$$\operatorname{rank}\begin{bmatrix} A & E^b \\ C & F^b \end{bmatrix} = n_x + n_s. \tag{5}$$

Table 2. Bank of subsets of faults defined for the pitch system.

	Subset S^1			Subset S^2			Subset S^3		
	$f^1[1]$	$f^1[2]$	$f^{\backslash 1}$	$f^2[1]$	$f^2[2]$	$f^{\backslash 2}$	$f^3[1]$	$f^3[2]$	$f^{\backslash 3}$
$f[1]$	×			×					×
$f[2]$		×				×	×		
$f[3]$			×		×			×	

For the case of study, the definition of the fault vectors f^b and $f^{\backslash b}$ of each b in the bank is detailed in Table 2. Note that the subset S^1 considers both sensor faults affecting each pitch system p (i.e., $f_{m(1),p}$ and $f_{m(2),p}$) whilst S^2 and S^3 consider the actuator fault together with each of these sensor faults (i.e., $f_{a,p}$ and $f_{m(1),p}$ or $f_{m(2),p}$). Condition (5) is verified for $b = 2$ and $b = 3$ and, then, it is possible to build a PI observer for estimating each of these subsets of faults. For $b = 1$, this condition is not verified. Below, we present a transformation which enhances the definition of observable inputs related to the faults in this subset.

3.2 Observable Inputs Related to Non-observable Subsets of Sensor Faults in Closed Loops

As stated in Section 3.1, condition (5) is not verified for the subset $b = 1$. Provided that $n_s = n_y$ and given that input (fault) observability is directly related to system invertibility (Hou and Patton (1998); Moylan (1977)), we study the transfer matrix between $f^1(s)$ and $y(s)$ in order to determine a subset of observable inputs related to the subset of faults included in vector f^1.

For the sake of clarity, let us consider the analogous case in which the close-loop feedback is the measurement provided by only one sensor, named after $\beta_{m,p}$, as depicted in Fig. 2 (instead of the average of the measurements provided by two redundant sensors $\beta_{m(1),p}$ and $\beta_{m(2),p}$). The transfer matrix of this simplified system satisfies

$$\beta_{m,p}(s) = \begin{bmatrix} G_0(s) & G_f(s) & G_v(s) \end{bmatrix} \begin{bmatrix} \beta_r(s) \\ f_{m,p}(s) \\ v_{m,p}(s) \end{bmatrix},$$

with

$$G_f(s) = G_v(s) = 1 - G_0(s) = \frac{s(s + 2\,\xi_0\,\omega_{n_0})}{s^2 + 2\,\xi_0\,\omega_{n_0}\,s + \omega_{n_0}^2}.$$

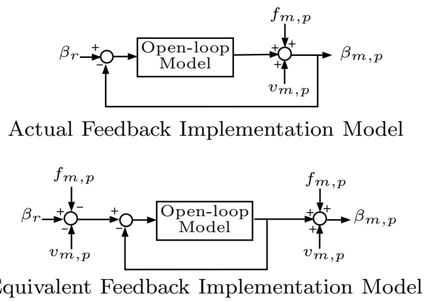

Fig. 2. Pitch system with one faulty and noisy sensor.

The derivative term in $G_f(s)$ ruins the realizability of inversing $G_f(s)$.

Remark 2. Any common control loop defined by $H(s)$ has unitary static gain (i.e., $H(0) = 1$). Then, the transfer function $H_f(s) = 1 - H(s)$ between a sensor fault inside a closed loop and the corresponding measurement verifies $H_f(0) = 0$, which ruins the realizability of inversing $H_f(s)$.

In order to get rid of the derivative term in $G_f(s)$, which causes the instability of the inverse of $G_f(s)$, we consider the derivative of fault $f_{m,p}(s)$, named after $\dot{f}_{m,p}(s)$, to be the fault input affecting $\beta_{m,p}$. Thus, $\beta_{m,p}(s)$ verifies

$$\beta_{m,p}(s) = \begin{bmatrix} G_0(s) & G'_f(s) & G_v(s) \end{bmatrix} \begin{bmatrix} \beta_r(s) \\ \dot{f}_{m,p}(s) \\ v_{m,p}(s) \end{bmatrix},$$

with

$$G'_f(s) = \frac{G_f(s)}{s} = \frac{s + 2\,\xi_0\,\omega_{n_0}}{s^2 + 2\,\xi_0\,\omega_{n_0}\,s + \omega_{n_0}^2}.$$

Note that the inverse of $G'_f(s)$ is realizable.

Provided these results, we define the subset $S^{1'}$ for the case of study. Vectors $f^{1'}$ and $f^{\backslash 1'}$ verify $f^{1'} = \left[\dot{f}_{m(1),p}\ \dot{f}_{m(2),p}\right]^T$ and $f^{\backslash 1'} = f_{a,p}$. The output $\beta_{m(1),p}$ satisfies

$$\beta_{m(1),p}(s) = \begin{bmatrix} G_0(s) \\ (1-G_0(s)/2)/s \\ -G_0(s)/2s \\ G_0(s)/\omega_{n_0}^2 \\ 1-G_0(s)/2 \\ -G_0(s)/2 \end{bmatrix}^T \begin{bmatrix} \beta_r(s) \\ \dot{f}_{m(1),p}(s) \\ \dot{f}_{m(2),p}(s) \\ f_{a,p}(s) \\ v_{m(1),p}(s) \\ v_{m(2),p}(s) \end{bmatrix} \qquad (6)$$

and similar applies to $\beta_{m(2),p}$. A minimal realization of the transfer matrix between the inputs in (6) and the output vector y can be written as

$$\dot{x}' = A'\,x' + B'\,u + E^{1'}\,f^{1'} + E^{\backslash 1'}\,f^{\backslash 1'} + G'\,v, \qquad (7a)$$

$$y = C'\,x' + F^{1'}\,f^{1'} + F^{\backslash 1'}\,f^{\backslash 1'} + H\,v, \qquad (7b)$$

with x' being the new state vector and A', B', C', $E^{1'}$, $F^{1'}$, $E^{\backslash 1'}$, $F^{\backslash 1'}$, G' and H' being the new state-space matrices. For system (7), the condition

$$\text{rank} \begin{bmatrix} A' & E^{1'} \\ C' & F^{1'} \end{bmatrix} = n_x + n_s$$

is verified and it is possible to build a PI observer for estimating the subset of inputs considered in $S^{1'}$.

Remark 3. When applying a PI observer in order to estimate the fault input vector $f^{1'}$, which contains the derivatives of the faults in f^1, we assume that $f^{1'}$ is continuously smooth with bounded first time derivative (i.e., the second time derivative of $f_{m(1),p}$ and $f_{m(2),p}$ is assumed to be bounded).

In Section 4, we present a bank of PI observers. Each of the estimators takes account on a different subset of fault inputs S^b with $b = 1', 2, 3$. Assuming certain constraint over the simultaneity of the faults occurrence, we build decision mechanisms which allow to feed a FA scheme with appropriate process and sensor fault estimates.

4. BANK OF ESTIMATORS AND DECISION MECHANISMS FOR FE

4.1 Bank of Estimators

Define each fault vector f^b with $b = 1', 2, 3$ to be represented as the auxiliary state system

$$\dot{\xi}^b = \zeta^b, \quad f^b = \xi^b,$$

where $\xi^b \in \mathbb{R}^{n_s}$ represents the fault state and $\zeta^b \in \mathbb{R}^{n_s}$ represents the fault smooth variations; then, (3) is augmented into

$$\dot{z}^b = \mathcal{A}^b\,z^b + \mathcal{B}^b\,u + \mathcal{D}^b\,\zeta^b + \mathcal{E}^b\,f^{\backslash b} + \mathcal{G}^b\,v, \qquad (8a)$$

$$y = \mathcal{C}^b\,z^b + \mathcal{F}^b\,f^{\backslash b} + \mathcal{H}^b\,v, \qquad (8b)$$

$$f^b = \mathcal{R}^b\,z^b, \qquad (8c)$$

with

$$z^b = \begin{bmatrix} x \\ \xi^b \end{bmatrix},\ \mathcal{A}^b = \begin{bmatrix} A^b & E^b \\ 0 & 0 \end{bmatrix},\ \mathcal{B}^b = \begin{bmatrix} B^b \\ 0 \end{bmatrix},\ \mathcal{D}^b = \begin{bmatrix} 0 \\ I \end{bmatrix},$$

$$\mathcal{E}^b = \begin{bmatrix} E^{\backslash b} \\ 0 \end{bmatrix},\ \mathcal{G}^b = \begin{bmatrix} G^b \\ 0 \end{bmatrix},\ \mathcal{C}^b = \begin{bmatrix} C^b & F^b \end{bmatrix},$$

$$\mathcal{F}^b = F^{\backslash b},\ \mathcal{H}^b = H^b,\ \mathcal{R}^b = [0\ \ I],$$

and

$$A^b = A',\ B^b = B',\ G^b = G',\ C^b = C',\ H^b = H' \quad \text{if } b = 1',$$
$$A^b = A,\ B^b = B,\ G^b = G,\ C^b = C,\ H^b = H \text{ if } b \in \{2, 3\}.$$

Each augmented state z^b is estimated by the following PI in the form of

$$\dot{\hat{z}}^b = \mathcal{A}^b\,\hat{z}^b + \mathcal{B}\,u + L^b\left(y - \mathcal{C}^b\,\hat{z}^b\right), \qquad (9a)$$

$$\hat{f}^b = \mathcal{R}^b\,\hat{z}^b + K^b\left(y - \mathcal{C}^b\,\hat{z}^b\right), \qquad (9b)$$

with L^b and K^b the gain matrices of the observer, which are to be defined. The fault estimation error $\tilde{f}^b = f^b - \hat{f}^b$ of such estimator becomes

$$\dot{\tilde{z}}^b = \mathbf{A}^b\,\tilde{z}^b + \mathcal{D}^b\,\zeta^b + \mathbf{E}^b\,f^{\backslash b} + \mathbf{G}^b\,v, \qquad (10a)$$

$$\tilde{f}^b = \mathbf{R}^b\,\tilde{z}^b + \mathbf{F}^b\,f^{\backslash b} + \mathbf{H}^b\,v, \qquad (10b)$$

where $\mathbf{A}^b = \mathcal{A}^b - L^b\,\mathcal{C}^b$, $\mathbf{E}^b = \mathcal{E}^b - L^b\,\mathcal{F}^b$ $\mathbf{G}^b = \mathcal{G}^b - L^b\,\mathcal{H}^b$, $\mathbf{R}^b = \mathcal{R}^b - K^b\mathcal{C}^b$, $\mathbf{F}^b = -K^b\,\mathcal{F}^b$ and $\mathbf{H}^b = K^b\,\mathcal{H}^b$. Applying the Laplace Transform to (10), we get

$$\tilde{f}^b(s) = \mathcal{G}^b_{\zeta^b}(s)\zeta^b(s) + \mathcal{G}^b_{f^{\backslash b}}(s)f^{\backslash b}(s) + \mathcal{G}^b_v(s)\,v(s), \qquad (11)$$

with $\mathcal{G}^b_{\zeta^b}(s) = \mathbf{M}^b(s)\mathcal{D}^b$, $\mathcal{G}^b_{f^{\backslash b}}(s) = \mathbf{M}^b(s)\mathbf{E}^b + \mathbf{F}^b$, $\mathcal{G}^b_v(s) = \mathbf{M}^b(s)\mathbf{G}^b + \mathbf{H}^b$ and $\mathbf{M}^b(s) = \mathbf{R}^b\,(sI - \mathbf{A}^b)^{-1}$. The error sources affecting the fault estimation error are not only the noises in v and the fault variations in ζ^b but also the ignored faults in $f^{\backslash b}$. Whilst v is zero-mean and ζ^b is bounded, no information regarding the faults in $f^{\backslash b}$ is knwon. Thus, an estimation f^b is only reliable when $f^{\backslash b} = 0$. In the following, we build decision mechanisms so as to decide wether $f^{\backslash b}$ is zero or not. Based on the results provided by these decision mechanisms, we define the estimates to be fed into the accommodation scheme.

Remark 4. Note that the proposed bank of estimators differs from well-known residual-based structures as the dedicated and generalized observer schemes in Chen and Patton (2012).

4.2 Reliable Estimations in the Bank

Note that in steady state and in the absence of noises, if a fault $f[i]$ is present in the system, we have that $\varphi^b[l](t)$, which is defined as

$$\varphi^b[l](t) = \begin{cases} \left|\hat{f}^b[l](t)\right| & \text{if } b \in \{2,3\}, \\ \left|\int_0^t \hat{f}^b[l](\tau)\, d\tau\right| & \text{if } b = 1', \end{cases} \quad (12)$$

verifies

$$\lim_{t\to\infty} \varphi^b[l](t) > 0 \quad \forall (b,l) : \pi^b[l] = i, \quad (13)$$

where we have assumed null initial conditions (i.e., $\hat{f}^{1'}[l](0) = 0$). Then, if there exists any b and l for which $\lim_{t\to\infty} \varphi^b[l](t) = 0$, it is because $f[\pi^b[l]] = 0$. The reliable estimators are thus the subset of estimators B for which the faults in $f^{\backslash b}$ are among the faults for which $\lim_{t\to\infty} \varphi^b[l](t) = 0$ at some b and l verifying $\pi^b[l] = i$. If n_s or more simultaneous faults are present in the system, there are no zero-value fault estimates because $f^{\backslash b} \neq 0$ for all b. This means that it is only possible to discern reliable estimates if condition

$$\#\{f[i] : f[i] \neq 0\} < n_s$$

is verified, i.e., the maximum number of simultaneous faults present in the system is $n_s - 1$.

Remark 5. In the absence of noises (i.e., $v = 0$), it is possible that $\varphi^b = 0$ even if the faults $f[l]$ verifying $l = \pi^b[l]$ are present in the system in the particular case in which $f^b = -\left(\mathbf{R}^b (\mathbf{A}^b)^{-1} \mathbf{E}^b + \mathbf{F}^b\right) f^{\backslash b}$ (which we obtained from (10) in steady state).

Provided the existence of noises, we have that $\varphi^b[l](t) > 0$ regardless of the presence of faults. Then, in order to decide which estimators are reliable, we define statistical thresholds, denoted as J_l^b, which take account on the effect of the noises on $\varphi^b[l](t)$. In all, we define the subset of reliable estimators at certain t as

$$B(t) = \{b : \pi^{\backslash b} \in I(t)\}, \quad (14)$$

with

$$I(t) = \left\{i : \left(\exists\, (b,l) : (\pi^b[l] = i, |\varphi^b[l](t)| < J_l^b)\right)\right\}, \quad (15)$$

where the thresholds J_l^b are to be defined.

Remark 6. Note that the presence of noises turns $\varphi^{1'}[l]$ to random walks. In order to avoid this effect, we propose to implement $\varphi^{1'}[l]$, which is defined in (12), as the integral of the estimates $\hat{f}^{1'}[l](t)$ exceeding certain threshold $J_l^{1'^*}$, i.e.,

$$\varphi^{1'}[l](t) = \left|\int_0^t \hat{f}^{1'}[l](\tau)\, (\hat{f}^{1'}[l](\tau) \geq J_l^{1'^*})\, d\tau\right|. \quad (16)$$

Moreover, one can reset $\varphi^{1'}[l](t)$ every instant of time t_0 (i.e., $\varphi^{1'}[l](t) = \left|\int_{t_0}^t \hat{f}^{1'}[l](\tau)\, (\hat{f}^{1'}[l](\tau) \geq J_l^{1'^*})\, d\tau\right|$) for which an actuator fault has been accommodated or for which the variables in $\varphi^2(t)$ and $\varphi^3(t)$ have not exceeded their thresholds since $t = t_0 - T_0$ with T_0 being an implementation design parameter.

Remark 7. It is possible that $|\varphi^b[l](t)| < J_l^b$ even if $f[\pi^b[l]](t) \neq 0$ in cases where the fault under consideration is not sufficiently large (i.e., $f[\pi^b[l]](t) < J_l^b$ for $b \in \{2,3\}$), varies slowly (i.e., $\dot{f}[\pi^{1'}[l]](t) < {J^{1'}}_l$) or due to the delay of the estimators in tracking the variation ξ^b. This means that the proposed FE scheme, which is based on a bank of estimators, requires sufficiently large faults and sufficiently enough time so as to ensure reliable FE.

4.3 FE Mechanism for FA

For FA, it is necessary to define the estimates of the faults $f_{a,p}$ and $f_{m,p} = f_{m(1),p} + f_{m(2),p}$.

Remark 8. For FA, it is not necessary to feed an estimate of each sensor fault $f_{m(1),p}$ and $f_{m(2),p}$ because $f_{m,p}$ is the variable to be accommodated. The reader may verify that vector $[f_{a,p}\ f_{m,p}]$ does not verify the condition for the construction of a PI observer, because $f_{m,p}$ is subject to the problem to which we referred in Section 3.2. Then, a scheme as the one presented in this work is necessary in order to get an appropriate estimate of $f_{m,p}$.

Provided the bank of estimators in the form of (9) and the decision mechanisms (14)-(15), we define the estimates of $f_{a,p}$ and $f_{m,p}$ as certain function of the reliable estimations regarding these faults:

$$\hat{f}_{a,p}(t) = \begin{cases} \hat{f}^3[2](t) & \text{if } 2 \notin B(t) \\ \hat{f}^2[2](t) & \text{otherwise} \end{cases}, \quad (17)$$

$$\hat{f}_{m,p}(t) = \begin{cases} \hat{f}^3[1](t) & \text{if } 2 \notin B(t) \\ \hat{f}^2[1](t) & \text{otherwise} \end{cases}, \quad (18)$$

with $\hat{f}^b[l]$ being the estimates for pitch p. The proposed scheme is outlined in Fig.3.

Remark 9. The proposed FE scheme does not require any complex reconstruction of the faults from the residuals provided FDI schemes. Moreover, only minor discontinuities may be introduced into the FA scheme when using the fault estimates provided by (17) and (18).

Remark 10. Note that it is an arbitrary decision whether to define $\hat{f}_{a,p}(t)$ as $\hat{f}_{a,p}(t) = \hat{f}^2[2](t)$ or $\hat{f}_{a,p}(t) = \hat{f}^3[2](t)$ when $\{2,3\} \in B(t)$ if the gain matrices (L^2, K^2), (L^3, K^3) and the thresholds J_2^2 and J_2^3 are designed in analogy. Note that, in this case, it would be possible to define $\hat{f}_{a,p}(t)$ as certain function g (e.g. the average) of $\hat{f}^2[2](t)$ and $\hat{f}^3[2](t)$. However, the function g would introduce a discontinuity in the FA scheme. Similar applies to $\hat{f}_{m,p}(t)$.

4.4 Design

For designing each pair of gain matrices L^b and K^b, we consider the existing trade-off between the attenuation of the effect of the fault variations ζ^b, the noises v and the ignored faults $f^{\backslash b}$ on the fault estimation error $\tilde{f}^b$ (see (11)). These attenuations describe, respectively, the fault tracking speed, the accuracy of the estimations in steady-state and the influence of the ignored faults on the estimations. Since (17) and (18) are based on estimators b for which $f^{\backslash b} = 0$, the attenuation of the effect of the

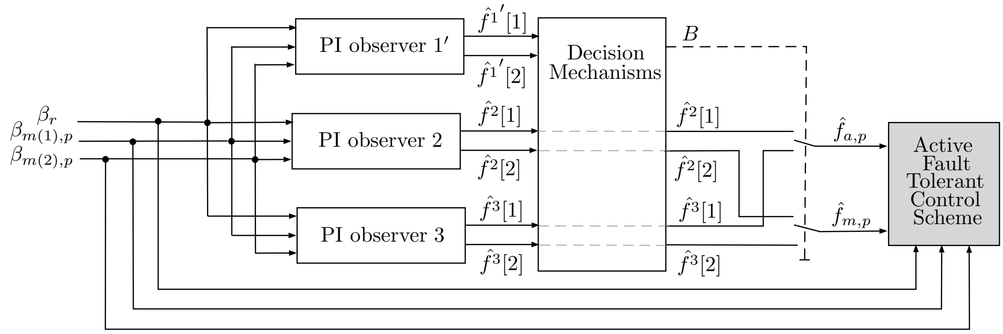

Fig. 3. FE for FA scheme in each pitch system.

ignored faults $f^{\backslash b}$ on the fault estimation error $\tilde{f}^b$ is not of interest. Thus, the design problem of the gain matrices of each PI observer (9) turns out to be one of the following minimization problems:

$$\begin{aligned} &\underset{L^b, K^b}{\text{minimize}} \quad \text{tr}(\Gamma_v^b) \\ &\text{subject to} \quad ||\mathcal{G}_v^b||_p \leq \Gamma_v^b \,, ||\mathcal{G}_{\zeta^b}^b||_p \leq \Gamma_{\zeta^b}^b \end{aligned} \tag{19}$$

or

$$\begin{aligned} &\underset{L^b, K^b}{\text{minimize}} \quad \text{tr}(\Gamma_{\zeta^b}^b) \\ &\text{subject to} \quad ||\mathcal{G}_v^b||_p \leq \Gamma_v^b \,, ||\mathcal{G}_{\zeta^b}^b||_p \leq \Gamma_{\zeta^b}^b \end{aligned} \tag{20}$$

where $||\cdot||_p$ denotes the $\mathcal{H}_p$ system norm (e.g., $\mathcal{H}_2$ or $\mathcal{H}_\infty$ system norm). In order to avoid major discontinuities in (17) and (18), we use the same performance constraints for banks $b = 2$ and $b = 3$ (i.e., $\Gamma_{\zeta^2}^2 = \Gamma_{\zeta^3}^3$ for (19) and $\Gamma_v^2 = \Gamma_v^3$ for (20)) . To solve this norm-based design problem, the preferred approach is to use linear matrix inequality (LMI) optimization techniques (Edwards et al. (2010)). Due to space restrictions, we do not include these formulation. See the literature (e.g., Boyd et al. (1994); Zhang et al. (2012)) for details on standard LMI formulation.

For designing the thresholds, note that if $f = 0$ (i.e., $\zeta^b = 0$ and $f^{\backslash b} = 0$), the noises v, which are zero-mean and Gaussian, are the only non-zero inputs in (10). Thus, $\hat{f}^b = -\tilde{f}^b$ is zero-mean, it has a Gaussian distribution and its steady-state covariance (i.e., $\Sigma^b = \lim_{t\to\infty} \mathbf{E}\{\hat{f}^b(t)\hat{f}^b(t)^T\}$) is given by the Lyapunov equations:

$$0 = \mathbf{A}^b\, \Xi + \Xi^T (\mathbf{A}^b)^T + \mathbf{G}^b\, V\, (\mathbf{G}^b)^T, \tag{21a}$$

$$\Sigma^b = \mathbf{R}^b\, \Xi\, (\mathbf{R}^b)^T + \mathbf{H}^b\, V\, (\mathbf{H}^b)^T, \tag{21b}$$

which we obtained from (10) with $\zeta^b = 0$ and $f^{\backslash b} = 0$. In all, we have that if $f = 0$, $\mathbb{P}\{|\hat{f}^b[l]| > \vartheta_l^b\} \leq \alpha$ with

$$\vartheta_l^b = \Phi_Z^{-1}(1 - \alpha/2)\sqrt{\Sigma^b[l,l]}$$

and $\Phi_Z^{-1}(\cdot)$ the inverse cumulative distribution function of a standard normal variable. Then, we define $J_l^b = \vartheta_l^b$ for $b \in 2, 3$ and $J_l^{b^*} = \vartheta_l^b$ for $b = 1'$. Provided the implementation of the variables $\varphi^{1'}[l]$ through (16) we fix $J_1^{1'} = J_1^2$ and $J_2^{1'} = J_1^3$.

Remark 11. As explained in the literature (e.g., Lan and Patton (2016); Lien (2004)), an integrated design of the FE and FA scheme must be performed whenever uncertainty is known to be present in the closed-loop system so as to ensure a correct performance of the control loop. This work is focused on the structure of the FE scheme rather than on its design, which can be performed following any other strategy.

Table 3. Benchmark fault scenario description.

	Fault signal	Fault type	Time occurrence
F1	$f_{m(1),1}$	fixed value	$t \in [2000, 2100]$ s
F2	$f_{m(2),2}$	gain factor	$t \in [2300, 2400]$ s
F3	$f_{m(1),3}$	fixed value	$t \in [2600, 2700]$ s
F4	$f_{a,2}$	change dynamics	$t \in [2900, 3000]$ s
F5	$f_{a,3}$	change dynamics	$t \in [3500, 3600]$ s

5. SIMULATION RESULTS

We validate the proposed FE by testing its behavior under the fault scenario of 4400 s defined in the benchmark (Odgaard et al. (2013)) and specified in Table 3. It is worth nothing that we used optimization problem (19) with coherent values $\Gamma_{\zeta^b}^b$ for the design of the gain matrices of the observer. We chose $\alpha = 1/1000$ for the design of the thresholds.

The first pitch system ($p = 1$) is affected by **F1**, which describes a fixed value on $\beta_{m(1),1}$ and causes an additive constant sensor fault $f_{m(1),1}$. Fig.4 shows the estimation results provided by the bank of estimators for pitch $p = 1$. In Fig.5, we include details on the estimation of the derivative of fault $f_{m(1),1}$, given by $\hat{f}^{1'}[1]$. For its part, Fig.6 shows the variables $\varphi^{1'}[1]$ and $\varphi^{1'}[2]$ computed through (16) for this pitch system. These variables together with the estimates of estimators $b = 2$ and $b = 3$ enhance the decision of wether each estimator b is reliable or not. Applying (14)-(15), we deduce that estimator $b = 3$ is not reliable because $\varphi^2[1](t) = \hat{f}^2[2]$ verifies $\varphi^2[1](t) \geq J_1^2$ and $\varphi^{1'}[1](t) \geq J_1^{1'}$. Applying the same procedure, estimator $b = 2$ appears to be reliable and provides the estimates of $f_{a,1}$ and $f_{m,1}$, as shown on left-hand side of Fig.8.

The second pitch system ($p = 2$) is affected by an hydraulic pressure drop represented by **F4** and it also suffers from **F2**, which consists on a gain factor on $\beta_{m(2),2}$ equal to 1.2 and causes a variable additive sensor fault $f_{m(2),2}$. Provided that the pitch reference is $\beta_r = 0$ during most of the time of these fault occurrence (see Odgaard et al. (2013) for details on the reference signals), only minor fault are estimated as shown in Fig.8, which includes the estimates $f_{a,2}$ and $f_{m,2}$ to be fed to the FA scheme.

Finally, the pitch $p = 3$ is affected by **F3** and **F5**, which describe, respectively, a fixed value on $\beta_{m(1),3}$ and an increased air content in the oil on the third pitch actuator. The actuator fault is slowly introduced during 30 s with a constant rate; afterwards, the fault is active during 40 s, and again decreases during 30 s. Fig.7 includes the

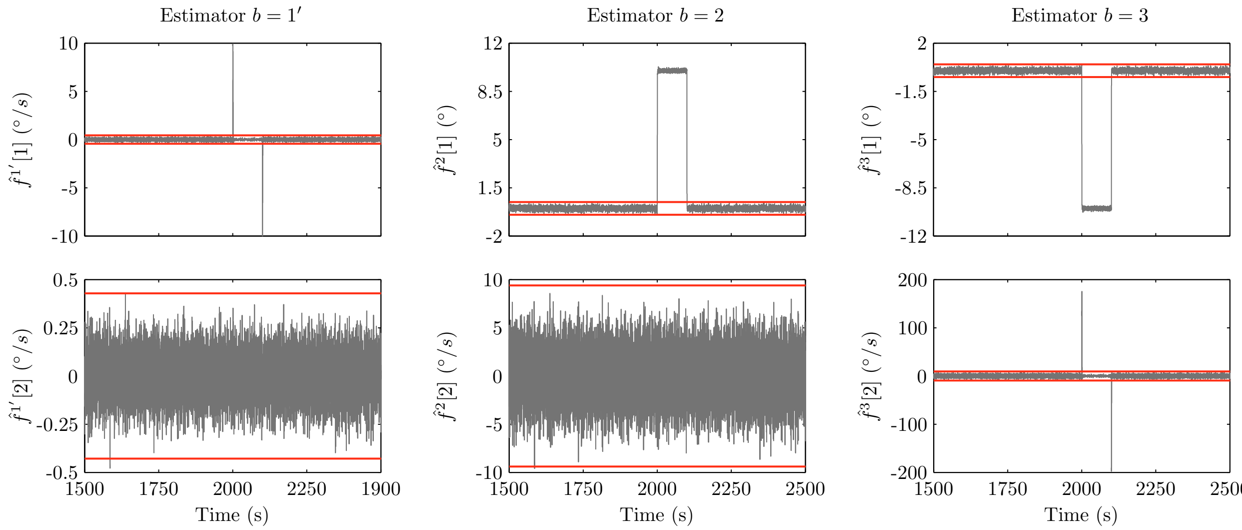

Fig. 4. Bank of estimators in the pitch system $p = 1$. (Grey: $\hat{f}^b[l]$, Red: J_l^b.)

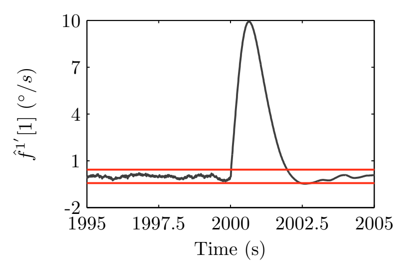

Fig. 5. Zoom on the estimation $\hat{f}^{1'}[1]$ in the pitch system $p = 1$. (Grey: $\hat{f}^{1'}[1]$, Red: $J_1^{1'}$.)

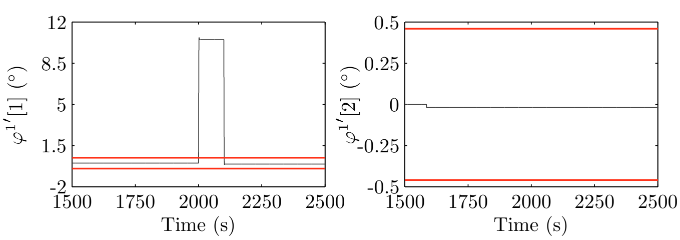

Fig. 6. Variables $\varphi^{1'}[1]$ and $\varphi^{1'}[2]$ computed through (16) in the pitch system $p = 1$. (Grey: $\varphi^{1'}[l]$, Red: $J_l^{1'^*}$.)

estimation results provided by the bank of estimators for pitch $p = 3$. If we apply, decision mechanisms (14)-(15) and definitions (17) and (18), we get the estimates $f_{a,1}$ and $f_{m,1}$ shown on right-hand side of Fig.8.

6. CONCLUSION

In this work, we have presented a fault estimator for the pitch system of wind turbines affected by both actuator and sensor faults. These faults do not verify input observability conditions because the number of sensors is limited and the sensor faults occur inside a close loop. Thus, we have proposed a scheme based on a bank of PI observers and decision mechanisms so as to provide appropriate fault estimates. The simulation results prove the effectiveness of the proposed methodology for FE in the pitch system of wind turbines. The proposed approach can be extended to achieve FE in other wind turbine systems such as the generator and drive train systems. The use of the fault estimates in an accommodation or active fault tolerant control scheme highlights as immediate future work. Future research will also include a more detailed design strategy, integrated within the accommodation scheme.

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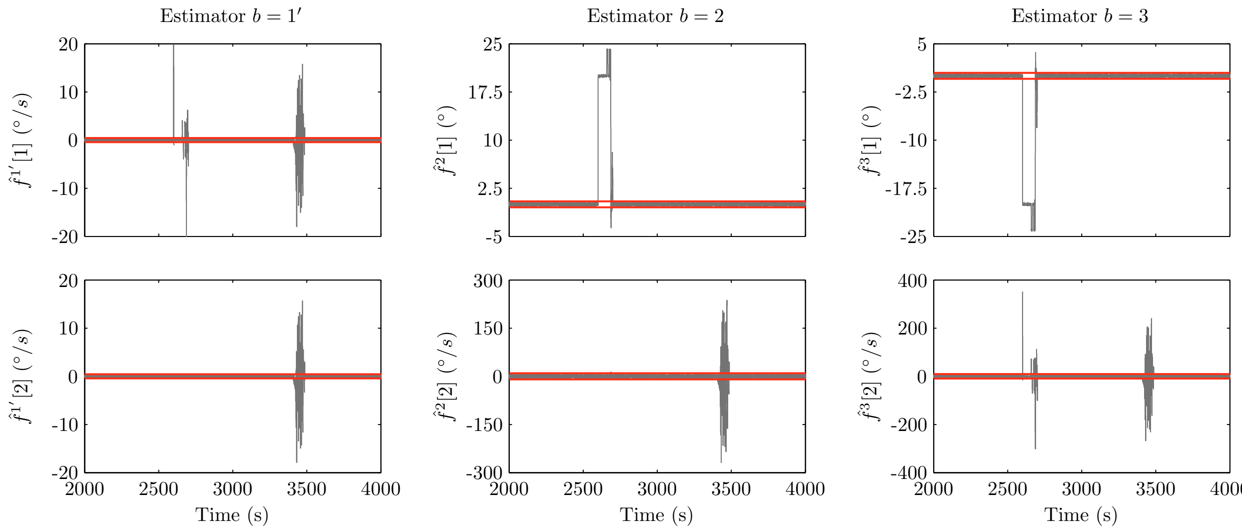

Fig. 7. Bank of estimators in the pitch system $p = 3$. (Grey: $\hat{f}^b[l]$, Red: J_l^b.)

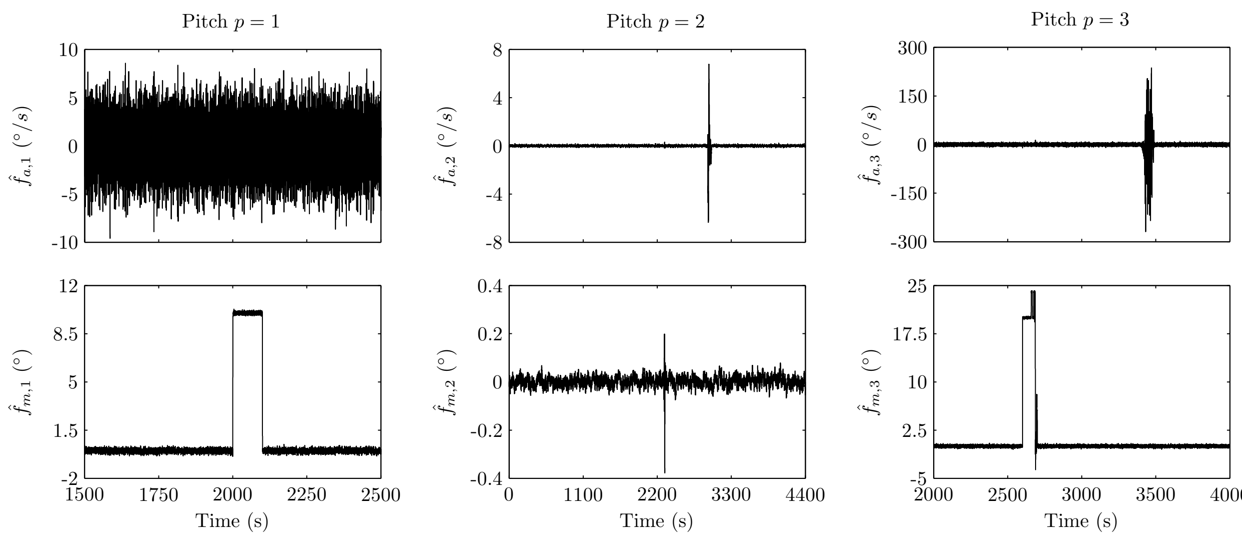

Fig. 8. FE in the pitch systems.

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