Integrated FDI/FTC approach for wind turbines using a LPV interval predictor subspace approach and virtual sensors/actuators

Houda Chouiref[1,2], Boumedyen Boussaid[1,3], Mohamed Naceur Abdelkrim[1], Vicenç Puig[2] and Christophe Aubrun[3]

Abstract

In order to keep wind turbines connected and in operation at all times despite the occurrence of some faults, advanced fault detection and accommodation schemes are required. To achieve this goal, this paper proposes to use the Linear Parameter Varying approach to design an Active Fault Tolerant Control for wind turbines. This Active Fault Tolerant Control is integrated with a Fault Detection and Isolation approach. Fault detection is based on a Linear Parameter Varying interval predictor approach while fault isolation is based on analysing the residual fault signatures. To include fault-tolerance in the control system (already available in the considered wind turbine case study based on the well known SAFEPROCESS benchmark), the information of the Fault Detection and Isolation approach block is exploited and it is used in the implementation of a virtual actuator and sensor scheme. The proposed Active Fault Tolerant Control is evaluated using fault scenarios which are proposed in the wind turbine benchmark to assess its performance. Results show the effectiveness of the proposed Active Fault Tolerant Control approach in faulty situation.

Keywords

Linear parameter varying, interval predictor, wind turbine, fault diagnosis, virtual sensor, virtual actuator

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Introduction

In the last years, wind turbines have become one of the important renewable energy sources. However, they can be affected by some fault scenarios which can lead to unsatisfactory performance in many works[1–4] theses faults are proposed. To avoid these consequences, fault tolerant control (FTC) strategies should be applied to keep the wind turbine operation and performance even under the case of faulty components or instruments. The development of FTC schemes for wind turbines has been already considered in the literature. The proposed approaches can be divided in two groups: active and passive. The passive approach takes into account the faults during the design of the control law[5] by considering them as uncertainties. This method is limited to small size fault scenarios and generally the obtained performance even in non-faulty scenarios is reduced.[6] This makes that the active fault tolerant control approach, that overcomes such limitations, has been largely developed. Active Fault Tolerant Control (AFTC) accommodates the fault using the information provided by a Fault Detection and Isolation (FDI) block.[7–9] Most of research in AFTC of wind turbines has focused on additive sensor and actuator faults using some type of observer scheme in fault detection.[10] In case of parametric faults, it is necessary to use some parameter estimation scheme that allows to obtain the new parameters after the fault and

[1]Modeling, Analysis and Control of Systems (MACS) Laboratory, National School of Engineers of Gabes, Gabes University, Gabes, Tunisia
[2]Institut de Robòtica i Informàtica Industrial (CSIC-UPC), Universitat Politècnica de Catalunya C/. Llorens i Artigas 4-6, Barcelona, Spain
[3]Centre de Recherche en Autoamtique de Nancyl (CRAN), University of Lorraine, Nancy, France

Corresponding author:
Boumedyen Boussaid, MACS Laboratory, National School of Engineers of Gabes, University of Gabes, Omar Ibn Khattab street, 6029, Zrig, Gabes, Tunisia.
Email: boumedyen.boussaid@enig.rnu.tn

accommodate/reconfigure the control loop accordingly (see e.g., Simani and Castaldi[11])

Regarding the application of FTC to wind turbines, there are many references considering the application FTC in generator[12,13] and drive train subsystems.[14] There are less references regarding the application to pitch subsystem despite it has an important role in producing an optimal power. The occurrence of a fault in this actuator causes a pitch position error which can result in an insufficient torque. Consequently, the power can not follow the reference set-point. In this work, the proposed fault tolerant method is applied to the pitch subsystem in the faulty case. Most of the FTC schemes for wind turbines have considered Linear Time Invariant (LTI) models.[15] However, wind turbines behave as nonlinear systems with complex dynamics specially when considering the aerodynamic part. Thus, the use of LTI models for designing FTC schemes for wind turbines could be insufficient to obtain satisfactory results. To overcome such limitations, recent FTC approaches have been proposed to use directly a nonlinear model[11,16,17] or some multiple-model scheme.[18,19]

Recently, Linear Parameter Varying (LPV) theory has become a standard formalism[20] for addressing the problem of control of nonlinear systems using pseudo-linear like methods. Many works have been developed using this approach and are applied to wind turbine systems. Wind turbines can be represented by an LPV model that is scheduled with some variables that define the operating point. For example, in Sloth et al.,[6] the LPV approach is used to design a fault-tolerant gain-scheduling controller.

The contribution of this paper is to propose an integrated FDI/FTC approach for wind turbines that solves the problem of control accommodation in case of actuator and sensor faults as the ones proposed in Zhang,[3] Odgaard and Stoustrup[21] and Laouti and Othman[4] and EL Bakri and Boumhidi[1] where the actuator faults are again not handled as well as the sensor faults. It seems to be a general trend of these solutions, which might indicate that the sensor faults in the benchmark model are easier to accommodate than the actuator faults. This approach combines LPV modeling and identification, robust FDI based on interval-based subspace approaches and virtual actuator/sensor FTC techniques (see Figure 1). This approach is applied to a wind turbine case study proposed as a FDI/FTC benchmark in Odgaard et al.[22]

This paper is organized as follows: In System description Section, the wind turbine benchmark system is detailed. In Fault detection and isolation Section, the fault diagnosis approach is presented and illustrated using the pitch system. In Fault tolerant control Section, the FTC method based on virtual sensor and actuator is described. Application results Section deals with simulation experiments that illustrate the implementation of the proposed approach using the proposed wind turbine benchmark and the comparison with existing results. Finally, Conclusion Section gives some concluding remarks.

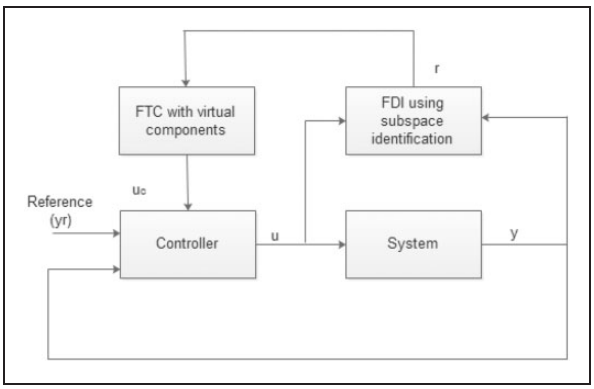

Figure 1. Principle of FTC scheme. (a) Pitch measurement and estimation, (b) Pitch residual, (c) Fault indicator.

Table 1. Wind turbine parameters.

Parameter	Notation	Value	Unit
Viscous friction	B_g	47,6	$\frac{MN.m.s}{rad}$
Torsion damping	B_{dt}	775.49	$\frac{MN.m.s}{rad}$
Friction coefficient	B_r	7.11	$\frac{MN.m.s}{rad}$
Gear ratio	N_g	95	
Torsion stiffness	K_{dt}	2.7 e9	$\frac{GN.m}{rad}$
Efficiency of the drive train	η_{dt}	0.97	
Generator inertia	J_g	390	$kg.m^2$
Rotor inertia	J_r	55 e6	$kg.m^2$
Time constant	α_{gc}	0.05 e-3	
Efficiency of the generator	η_{gc}	0.98	
Radius of blades	R	57.5	m^2
Air density	ρ	1.225	$\frac{kg}{m^3}$
Damping ratio	ζ	0.6	$\frac{rad}{s}$
Natural frequency	ω_n	11.11	$\frac{rad}{s}$

System description

As discussed in the introduction, the purpose of this paper is to develop an integrated FDI/FTC scheme based on the LPV approach for wind turbines and illustrate it applied to the benchmark case study proposed in Odgaard and Stoustrup.[10] The parameters of this case of wind turbine in nominal case are given in the Table 1.[23]

The model of the considered wind turbine is composed of four subsystems: Aerodynamics, Pitch, Drive train and Generator which are described in the following subsections.

Aerodynamics

The wind turbine aerodynamics is modeled as a torque acting on the blades. This torque, T_r, is given by:[22]

$$T_r(t) = \frac{\rho \pi R^3 C_q(\lambda(t), \beta_j(t)) v_w(t)^2}{6} \tag{1}$$

where λ is the tip speed ratio, ρ is the density of the air, R is the radius of blades, v_w is the wind speed, β_j is the angle of the pitch of the blade j and C_q is the coefficient of the torque.

Drive train

The drive train is modeled with a flexible two mass system and is used to increase the speed from rotor to generator. The model of the drive train is given as:[6]

$$\begin{bmatrix} \dot{w}_r(t) \\ \dot{w}_g(t) \\ \dot{\theta}_\Delta(t) \end{bmatrix} = A_d \begin{bmatrix} w_r(t) \\ w_g(t) \\ \theta_\Delta(t) \end{bmatrix} + B_d \begin{bmatrix} T_r(t) \\ T_g(t) \end{bmatrix} \tag{2}$$

where w_r,w_g,θ_Δ,T_r,T_g are respectively the rotor speed, the generator speed, the torsion angle, the rotor and generator torque.The system matrices in (2) are given by

$$A_d = \begin{bmatrix} -\frac{B_{dt}+B_r}{J_r} & \frac{B_{dt}}{N_g J_r} & -\frac{K_{dt}}{J_r} \\ \frac{\eta_{dt} B_{dt}}{N_g J_g} & \frac{-\frac{\eta_{dt}+B_{dt}}{N_g^2} - B_g}{J_g} & \frac{\eta_{dt} K_{dt}}{N_g J_g} \\ 1 & \frac{-1}{N_g} & 0 \end{bmatrix} \text{ and}$$

$$B_d = \begin{bmatrix} \frac{1}{J_r} & 0 \\ 0 & -\frac{1}{J_g} \end{bmatrix}$$

Generator

The dynamics of the converter is modeled by a first order transfer function[22]

$$\frac{T_g(s)}{T_{rg}(s)} = \frac{\alpha_{gc}}{s + \alpha_{gc}} \tag{3}$$

The generator produces a power which is given by

$$P_g(t) = \eta_{gc} w_g(t) T_g(t) \tag{4}$$

Pitch

The hydraulic pitch in this benchmark wind turbine is a piston servo mechanism which can be modeled by a second order transfer function as follows:[22]

$$\frac{\beta(s)}{\beta_r(s)} = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \tag{5}$$

where β_r corresponds to the reference values of pitch angles, w_n and ξ are respectively the natural frequency and the damping ratio. These parameters are variable with hydraulic pressure P.[22] Then, the representation of the pitch system can be represented by means of the following LPV model which combine the normal and the faulty operation mode according to Sloth et al.[6] using P as the scheduling variable μ:

$$x(k+1) = A(\mu)x(k) + B(\mu)u(k) \tag{6}$$

$$y(k) = Cx(k) \tag{7}$$

with

$$A(\mu) = \begin{bmatrix} 1 & T_e \\ -T_e w_n^2(\mu) & -2T_e\xi(\mu)w_n(\mu) + 1 \end{bmatrix} \text{ and}$$

$$B(\mu) = \begin{bmatrix} 0 \\ T_e w_n^2(\mu) \end{bmatrix}$$

with $T_e = 0.001$, The state vector includes the pitch angular speed and the position and the output measurement is the angle.

Fault detection and isolation

In the proposed AFTC presented in Figure 1, the FDI module is based on passive robust approach that combines the LPV subspace estimation approach proposed in Van Willem and Verhagen[24] and the interval predictor approach introduced in Puig.[25]

Interval predictor approach

This approach is used to consider the modelling uncertainty and allow to introduce robustness in the fault detection block. The uncertainty in the model is assumed to be concentrated in the parameters that are assumed unknown but bounded by a set Θ that is described by a zonotope:

$$\Theta = \theta^0 \oplus HB^n = \{\theta^0 + Hz : z \in B^n\} \tag{8}$$

where θ^0 is the nominal model, H is matrix uncertainty shape, B^n is a unitary box composed of n unitary interval vectors $(B = [-1, 1])$ and $\oplus$ is the Minkowski sum. In this paper, a particular parameter set Θ which is bounded by an interval box is used:

$$\Theta = [\underline{\theta}_1, \overline{\theta}_1] \times \ldots [\underline{\theta}_i, \overline{\theta}_i] \times \ldots [\underline{\theta}_{n_\theta}, \overline{\theta}_{n_\theta}] \tag{9}$$

where $\underline{\theta}_i = \theta_i^0 - \lambda_i$ and $\overline{\theta}_i = \theta_i^0 + \lambda_i$ with $\lambda_i \geq 0$ and $i = 1, \ldots, n_\theta$. The interval box can be represented by means of a zonotope with center θ^0 and H equal to an $n_\theta \times n_\theta$ diagonal matrix:

$$\theta^0 = \left(\frac{\overline{\theta}_1 + \underline{\theta}1}{2}, \frac{\overline{\theta}_2 + \underline{\theta}2}{2}, \ldots, \frac{\overline{\theta}_{n_\theta} + \underline{\theta}n_\theta}{2} \right) \tag{10}$$

$$H = diag(\lambda_1, \lambda_2, \ldots, \lambda_{n_\theta}) \tag{11}$$

The model can be described by the following regressor form:

$$y(k) = \phi(k)\theta(k) + e(k) \tag{12}$$

where $\phi(k)$ is the regressor vector that is function of inputs $u(k)$ and outputs $y(k)$, $\theta(k) \in \Theta$ is the parameter vector, Θ is the set of parameters and $e(k)$ is the noise term assumed unknown but bounded $|e(k)| \leq \sigma$.

Using this approach, the measured data in fault-free case are covered by the interval predicted output.

$$y(k) \in [\underline{\hat{y}(k)} - \sigma, \overline{\hat{y}(k)} + \sigma] \tag{13}$$

where

$$\underline{\hat{y}(k)} = \hat{y}^0(k) - ||\phi(k)H||_1 \tag{14}$$

$$\overline{\hat{y}(k)} = \hat{y}^0(k) + ||\phi(k)H||_1 \tag{15}$$

and $\hat{y}^0(k)$ is the prediction with nominal parameters with $\theta^0 = [\theta_1, \theta_2, \ldots, \theta_{n_\theta}]^T$ obtained using the parameter estimation method presented here after

$$\hat{y}^0(k) = \phi(k)\theta^0 \tag{16}$$

Estimation approach

Problem formulation. to estimate the nominal LPV parameters in (8) using the subspace method proposed in Van Willem and Verhagen[24] this model is expressed as follows:

$$x(k+1) = \sum_{i=1}^{m} \mu^{(i)}(k)(A^{(i)}x(k) + B^{(i)}u(k) + K^{(i)}e(k)) \tag{17}$$

$$y(k) = Cx(k) + Du(k) + e(k) \tag{18}$$

where $u(k) \in R^r, x(k) \in R^n, y(k) \in R^l$ are the input, state and output vectors over time $k = \{1, \ldots, N\}$ and the noise process $e(k)$ is a zero-mean white sequence and m is the number of scheduling parameters (or local models) that are supposed to be measurable in real time. The vector of scheduling parameters is defined as follows:

$$\mu(k) = \left[1, \mu^{(2)}(k), \ldots, \mu^m(k)\right]^T$$

Then, equations (17) and (18) can be rewritten in the predictor form as:

$$x(k+1) = \sum_{i=1}^{m} \mu^{(i)}(k)(\tilde{A}^{(i)}x(k) + \tilde{B}^{(i)}u(k) + K^{(i)}y(k)) \tag{19}$$

with

$$\tilde{A}^{(i)} = A^{(i)} - K^{(i)}C$$
$$\tilde{B}^{(i)} = B^{(i)} - K^{(i)}D$$

Problem solution. Defining $z(k) = \left[u(k)^T, y(k)^T\right]^T$, $X = [x(p+1), \ldots, x(N)]$ and

$$\overline{z}^p(k) = \begin{bmatrix} z(k) \\ z(k+1) \\ . \\ . \\ . \\ z(k+p-1) \end{bmatrix}$$

where p is a past window length. By introducing the matrix

$$P_{p/k} = \mu(k+p-1) \otimes \ldots \otimes \mu(k) \otimes I_{r+l}$$

we can define

$$N_k^p = \begin{bmatrix} P_{p/k} & . & . & . & 0 \\ . & P_{p-1/k+1} & & & \\ . & & . & & \\ . & & & . & \\ 0 & & & & P_{1/k+p-1} \end{bmatrix}$$

Then, the matrices U, Y and Z are defined as follows

$$U = [u(p+1), \ldots, u(N)] \tag{20}$$

$$Y = [y(p+1), \ldots, y(N)] \tag{21}$$

$$Z = \left[N_1^p \overline{z}^p(1), \ldots, N_{N-p+1}^p \overline{z}^p(N-p+1)\right] \tag{22}$$

The controllability matrix can be expressed as:

$$\kappa^p = [l_p, \ldots, l_1]$$

with

$$l_1 = \left[\overline{B}^{(1)}, \ldots, \overline{B}^{(m)}\right]$$

and

$$l_j = \left[\tilde{A}^{(1)} l_{j-1}, \ldots, \tilde{A}^{(m)} l_{j-1}\right]$$

with $\overline{B}^{(i)} = [\tilde{B}^{(i)}, K^{(i)}]$

If the matrix $\left[Z^T, U^T\right]$ has full row rank, we can estimate the matrices $C\kappa^p$ and D by solving the next linear regression problem[26]

$$\min_{C\kappa^p, D} ||Y - C\kappa^p Z - DU||_F^2 \tag{23}$$

where $||\cdot||_F$ is the Frobenius norm.As in the case of LTI system identification, this problem can be solved for the considered type of LPV systems by using traditional least square methods.[27]

According to literature,[28,29] if the matrix $\left[Z^T \quad U^T\right]$ has full row rank, the equation (23) has a unique solution and is given by

$$\left[C\hat{\kappa}^p \quad \hat{D}\right] = Y\left[Z^T \quad U^T\right]\left(\begin{bmatrix} Z \\ U \end{bmatrix}\left[Z^T \quad U^T\right]\right)^{-1} \tag{24}$$

When p is large, the solution is computed by using the SVD of the matrix:

$$\begin{bmatrix} Z \\ U \end{bmatrix} = \left[\upsilon \quad \upsilon_\perp\right]\begin{bmatrix} \sum_m & 0 \\ 0 & 0 \end{bmatrix}\begin{bmatrix} V^T \\ V_\perp^T \end{bmatrix} \tag{25}$$

The solution obtained when minimizing the norm is given by:

$$\left[C\hat{\kappa}^p \quad \hat{D}\right] = YV\sum\nolimits_m^{-1} \upsilon^T \tag{26}$$

To evaluate the performance of the identified system, we use the Variance-Accounted-For (VAF) value which is defined as:

$$VAF(y(k), \hat{y}(k)) = \max\left\{1 - \frac{\mathrm{var}(y(k) - \hat{y}(k))}{\mathrm{var}(y(k))}, 0\right\} \times 100\% \tag{27}$$

where $var()$ denotes the variance, $\hat{y}(k)$ and $y(k)$ are respectively the estimated and real system outputs.

Parameter uncertainty estimation

Once the nominal LPV parameters in (8) have been obtained using the subspace method recalled in previous section, to characterize the parameter set Θ, defined in (9) consistent with the data collected in a fault-free scenario, the bounds (11) should be obtained. The uncertain parameter estimation algorithm proceeds by solving the following optimization problem:

$$\begin{aligned} &\min \sum_{i=1}^{n_\theta} \lambda_i^2 \\ &\text{subject to :} \\ &\quad y_i(k) \in \left[\underline{\hat{y}}_i(k) - \sigma_i, \overline{\hat{y}}_i(k) + \sigma_i\right] \\ &\quad \overline{\hat{y}}(k) = \hat{y}^0(k) + ||\phi(k)H||_1 \\ &\quad \underline{\hat{y}}(k) = \hat{y}^0(k) - ||\phi(k)H||_1 \\ &\quad \hat{y}^0(k) = \phi(k)\theta^0 \\ &\quad H = diag(\lambda_1, \lambda_2, \ldots, \lambda_{n_\theta}) \\ &\quad \text{For all } i = 1, \ldots, n_y \text{ and } k = 1, \ldots, N \end{aligned} \tag{28}$$

To summarize, the proposed uncertain LPV subspace identification approach is described in Algorithm 1.

Algorithm 1 LPV uncertain parameter estimation

1: Create the matrices U and Z using (20).
2: Obtain the SVD decomposition (25) of U and Z.
3: Solve the linear problem in (23) using (26) and obtain nominal parameters θ^0
4: Estimate the parameter uncertain bounds solving the optimization problem (28)

Fault isolation scheme

The fault isolation will be designed considering the set of faults proposed in the wind turbine benchmark case study[30] that are described in the following taking into account their type:

- **Sensor faults**. The first sensor fault scenario considered affects the pitch position measurements, which is denoted as $\Delta\beta_m$. The second fault scenario corresponds to the rotor speed measurement and is denoted as $\Delta w_{g,m}$ and $\Delta w_{r,m}$. These faults are either electrical or mechanical faults, and can be classified as a fixed value or a gain factor on the measurements. These sensor faults cause a false measurement that affects the performance of the control law.
- **Actuator faults**. Actuator faults may occur in the pitch actuator or in the converter. In the first subsystem, faults results in a change of dynamics either due to dropped pressure or high air content

Table 2. Faults affecting benchmark system.

No	Fault type	Symbol	Type
f_1	Sensor	$\Delta\beta_{1,m1}$	Fixed values
f_2	Sensor	$\Delta\beta_{2,m1}$	Gain factor
f_3	Sensor	$\Delta w_{r,m1}$	Fixed values
f_4	Sensor	$\Delta w_{r,m2}$	Gain factor
f_5	Sensor	$\Delta w_{g,m1}$	Fixed values
f_6	Sensor	$\Delta w_{g,m2}$	Gain factor
f_7	Actuator	ΔT_g	Offset
f_8	Actuator	$\Delta\beta$(hydraulic)	Dynamic change
f_9	Actuator	$\Delta\beta$(Air in oil)	Dynamic change
f_{10}	System	$\Delta w_g, \Delta w_r$	Dynamic change

in the oil. These faults are denoted as $\Delta\beta$. In the second subsystem, faults manifests through an additive offset. The cause of this fault is an offset in the internal converter control loop. These faults are denoted as ΔT_g. Faults in actuator of the wind turbine caused slow control actions.

- **System faults**. The considered system faults occur in the drive train, where the friction changes with time. These faults are denoted as Δw_r and Δw_g. This type of fault is not that severe, but it is an indication of the wear of the drive train, which finally results in its total breakdown. This system fault increases the level of drive train vibrations.

All these faults are summarized and listed in Table 2. Since the control system can be sensitive to different type of faults, a fault isolation is needed to localize the type of fault occurring in the wind turbine.

Using the sensors available in the wind turbine benchmark and the model presented in Section 2, the following residuals can be obtained applying structural analysis and the perfect matching algorithm[8]

$$\begin{aligned}
r_1(k) &= w_{rm1}(k) - w_{rm2}(k)\\
r_2(k) &= w_{rm2}(k) - \widehat{w}_{rm2}(k)\\
r_3(k) &= w_{gm1}(k) - w_{gm2}(k)\\
r_4(k) &= w_{gm2}(k) - \widehat{w}_{gm2}(k)\\
r_5(k) &= \beta_{1m1}(k) - \beta_{1m2}(k)\\
r_6(k) &= \beta_{1m2}(k) - \widehat{\beta}_{1m2}(k)\\
r_7(k) &= \beta_{2m1}(k) - \beta_{2m2}(k)\\
r_8(k) &= \beta_{2m2}(k) - \widehat{\beta}_{2m2}(k)\\
r_9(k) &= \beta_{3m1}(k) - \beta_{3m2}(k)\\
r_{10}(k) &= \beta_{3m2}(k) - \widehat{\beta}_{3m2}(k)\\
r_{11}(k) &= \tau_{gm}(k) - \widehat{\tau}_g(k)\\
r_{12}(k) &= P_{gm}(k) - \eta_g w_{gm2}(k)\tau_{gm}(k)
\end{aligned} \tag{29}$$

Table 3. Fault signature matrix.

	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}
R_1			×	×						
R_2	×	×					×	×	×	×
R_3					×	×				
R_4	×	×					×	×	×	×
r_5	×									
r_6	×							×		
r_7		×								
r_8		×							×	
r_9										
r_{10}										
r_{11}							×			
r_{12}							×			×

Then, fault detection will be based on checking if (13) is satisfied. In case that, it is not satisfied a fault can be indicated. Otherwise, nothing can be said. It is carried out on the basis of fault signatures, generated by the detection module, and their relation with all the considered faults, $f(k) = \{f_a(k), f_y(k)\}$. The result of the fault detection test (13) allows obtaining a set of *fault signatures* $\psi(k) = [\psi_1(k), \psi_2(k), \ldots, \psi_{ny}(k)]$, where each fault indicator is given by:

$$\psi_i(k) = \begin{cases} 0 & \text{if} \quad y(k) \in [\underline{\hat{y}(k)} - \sigma, \overline{\hat{y}(k)} + \sigma] \\ 1 & \text{if} \quad y(k) \notin [\underline{\hat{y}(k)} - \sigma, \overline{\hat{y}(k)} + \sigma] \end{cases} \tag{30}$$

Then, the binarized residuals are matched against the fault signature denoted as M and presented in Table 3. An element $m_{i,j}$ of M is equal to 1 if the fault f^j affects the computation of the residual r_i; otherwise $m_{i,j} = 0$. A column of M is known as a *theoretical fault signature* and indicates which residuals are affected by a given fault.

The procedure accepted as standard by the FDI community involves finding a matching between the observed fault signature and one of the theoretical fault signatures. However, this reasoning is not appropriate for variables varying in the time but bounded. Due to the uncertainty, when a fault is present in the system, an undefined number of the residuals affected by the fault can be found inconsistent, mainly depending on the sensitivity of each residual with respect to the fault and on the fault magnitude. In other words, the observed fault signature will not exactly match the theoretical signature of the present fault. In this case, if the column-matching procedure is used, then the particular fault will not be identified. An appropriate reasoning should only consider the residuals that are inconsistent when searching for the fault (inconsistency is relevant, consistency is not). A residual that is found inconsistent indicates that one of the faults that affect the residual is acting on the system. But the contrary is not true, if a

residual is satisfied, it does not assure that none of the associated faults is present. According to the established terminology, the used algorithm must avoid *single-fault exoneration* (which is implicit in the column matching reasoning). Under single-fault assumption, this can be easily achieved by taking into account that the fault that is actually present in the system has to affect all the residuals that have been found inconsistent according to the observed fault signature (if not, the single fault hypothesis can not explain the observed behavior). Algorithm 2 summarizes an isolation procedure based on this idea.

Algorithm 2 fault detection and isolation

```
fault ← FALSE
k ← 0
while fault ≠ TRUE do
  k ← k + 1
  Obtain input-output data {u(k), y(k)} at time instant k
  Compute ŷ(k) using (17)-(18) for each submodel in residual expressions (29) with the parameters adjusted with the parameter estimation algorithm in Section 3.2
  for i = 1 to n_y do
    if y_i(k) ∈ [ŷ_i(k) − σ, ŷ_i(k) + σ] then
      ψ_ik = 1
      fault ← TRUE
    else
      ψ_ik = 0
    end if
  end for
  FC ← {f^1, f^2, ..., f^{n_f}}
  for i = 1 to n_y do
    if ψ_ik = 1 then
      for j = 1 to n_f do
        if m_{i,j} = 0 then
          FC ← FC − f^j
      end if
      end for
    end if
  end for
end while
Fault candidate set FC
```

Fault tolerant control

Introduction

In terms of control, the wind turbine works in two regions: At low wind speeds, in the partial load region, the turbine is controlled to maximize the power output that is achieved by adjusting the generator torque to obtain an optimum ratio between the wind speed and the tip speed of the blades which is considered in Kamal and Aitouche.[31] At higher wind speeds, in the full load region, the wind turbine is controlled to reduce loads by producing a rated power output at a constant rotor speed, which is obtained by pitching the blades to adjust the efficiency of the rotor.[11] In this paper, the problem of control by pitching the blade will be treated applying a constant generator torque where the speed or a power PI controller can be used depending on the operating region. The LPV theory has already been proposed for designing controller in non faulty case. But, recently, it has also been used for FTC design.[32–35]

In this work, fault tolerance has been included in the wind turbine control system by designing virtual sensors and actuators using the LPV model of the wind turbine. The goal of the FTC strategy, based on virtual sensors/actuactors, is to hide the fault to the controller to obtain the nominal property. When a fault occurs, this approach is based on inserting a block between the faulty plant and the nominal controller to allow the controller to see the plant like is in the non faulty case. This block can be a virtual actuator or virtual sensor according to the fault type. Using this method with virtual components, the nominal controller is kept and only the faulty plant will be reconfigured. In actuator faulty case, the new signal control is obtained from the output of the nominal controller considering the fault scenario. In case of virtual sensors, the reconfiguration block uses the faulty plant output as input and compute the fault free one. This hiding approach have many advantages:[36]

- Whatever the nominal regulator, this method can be used.
- In the case of partial fault effect, using this design, it is not necessary to redesign the controller.
- In the case of a human operator, this design reduces its efforts and stress.

LPV virtual sensor/actuator

In the following, a simplified explanation of virtual sensor and actuator is provided (for a more detailed description, see Blanke et al.[8])

Virtual actuator. From the conceptual point of view, the idea is that by means of the virtual actuator block, the transfer function of the faulty plant behaves as in non-faulty situation:

$$G_a(s)G_f(s) = G_n(s) \tag{31}$$

where G_a, G_f, G_n are respectively the transfer function of virtual actuator, faulty and nominal plant.

In case of considering the LPV model of the wind turbine, the implementation should be done using the state-space representation

$$\dot{x}(t) = A(\mu)x(t) + B_f(\mu)u(t) \tag{32}$$

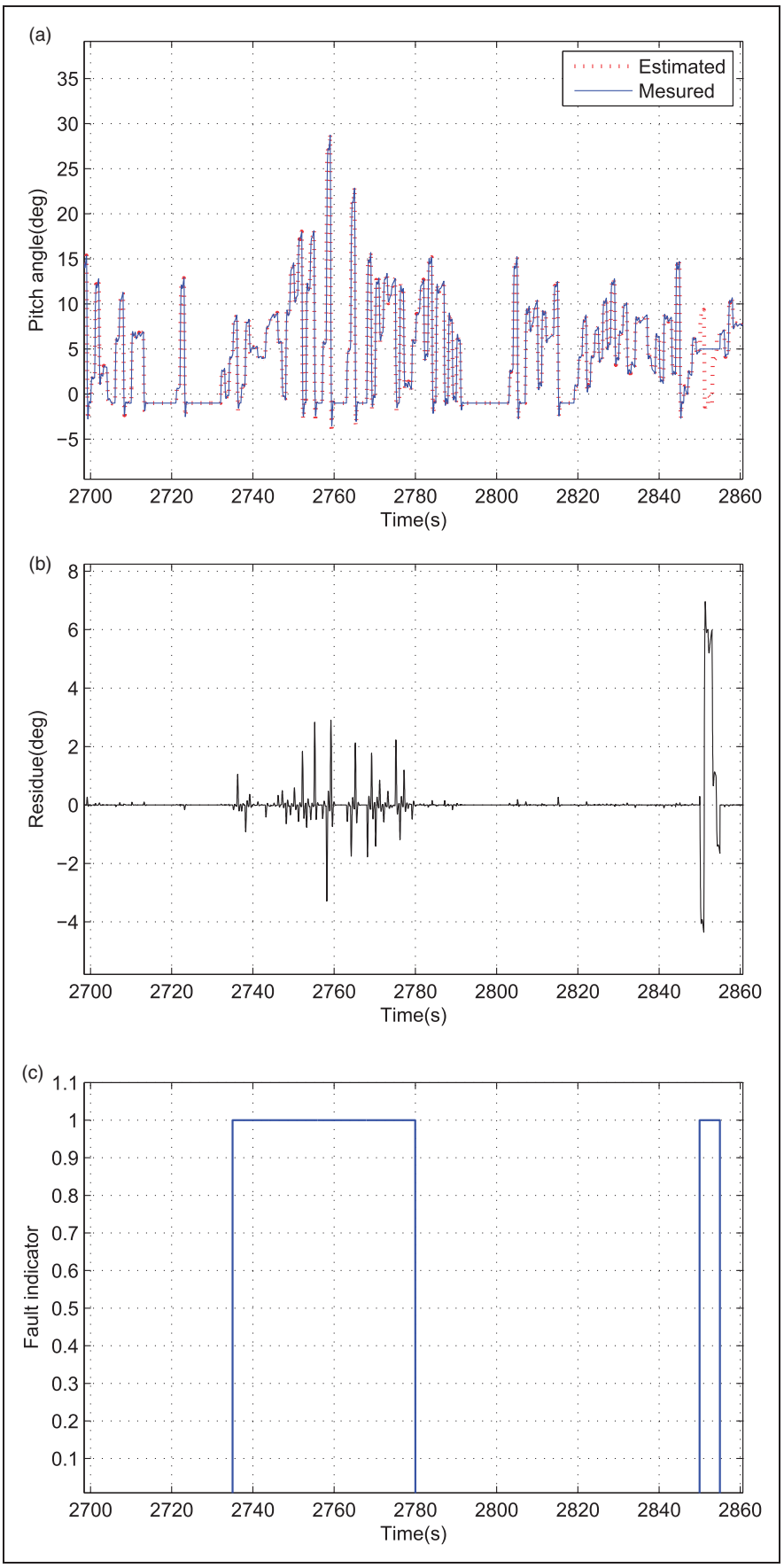

Figure 2. Fault detection results. (a) Pitch measurement and estimation, (b) Error between real and desired signal.

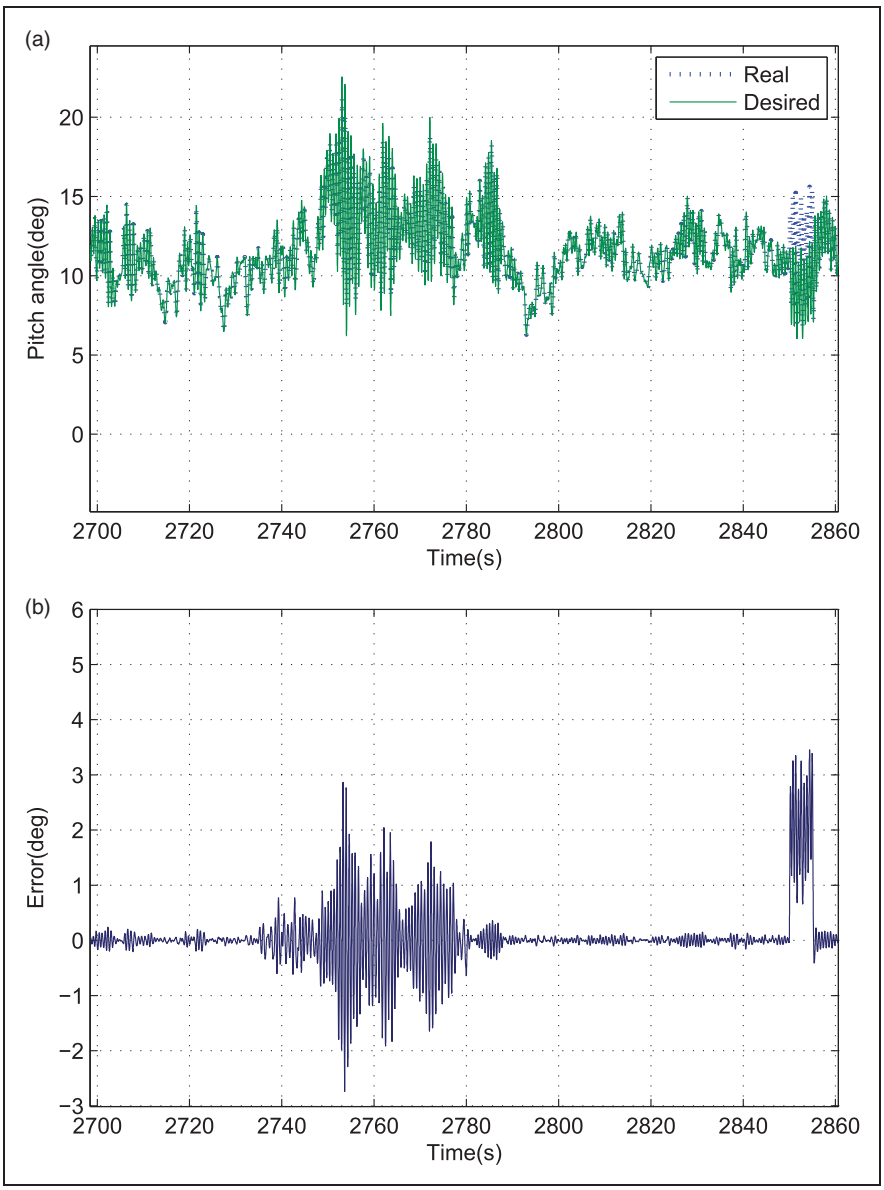

Figure 3. System response in case of fault without FTC.

where $B_f = B(\mu)diag(\psi_1 \ldots \psi_{nu})$, ψ_i is the effectiveness of the ith actuator, $\psi_i \in [0, 1]$.

If rank $(B_f) =$ rank (B), the new control signal is obtained by

$$u_{FTC}(t) = N(\mu)u_n(t) \tag{33}$$

where u_n is the output of the controller, $N(\mu) = B_f^+ B$ with B_f^+ is the pseudo inverse of B_f.

Virtual sensor. Considering the output equation in sensor fault case

$$\dot{x}_f(t) = A(\mu)x_f(t) + Bu(t) \tag{34}$$

$$y_f(t) = C_f(\gamma)x_f(t) + f_y(t) \tag{35}$$

$$y_{FTC}(t) = P()(y_f(t) - f_y(t)) \tag{36}$$

where $C_f = diag(\gamma_1 \ldots \gamma_{ny})C$, γ_i is the effectiveness of the ith sensor, $\gamma_i \in [0, 1]$.

If rank$(C_f(\gamma))=$ rank$\begin{pmatrix} C \\ C_f \end{pmatrix}$, the new signal is obtained as follows.

$$y_{FTC}(t) = P(\gamma)(y_f(t) - f_y(t)) \tag{37}$$

where $P = CC_f^+$ with C_f^+ is the pseudo inverse of C_f.

Application to the wind turbine benchmark

To illustrate the use of the virtual actuator and sensor FTC schemes, the case of the two fault scenarios proposed in the wind turbine benchmark[22] are used.

Actuator fault. In case of the pitch actuator fault scenario proposed in the wind turbine benchmark,[22] a change in the parameters ξ and w_n of (5) occurs.

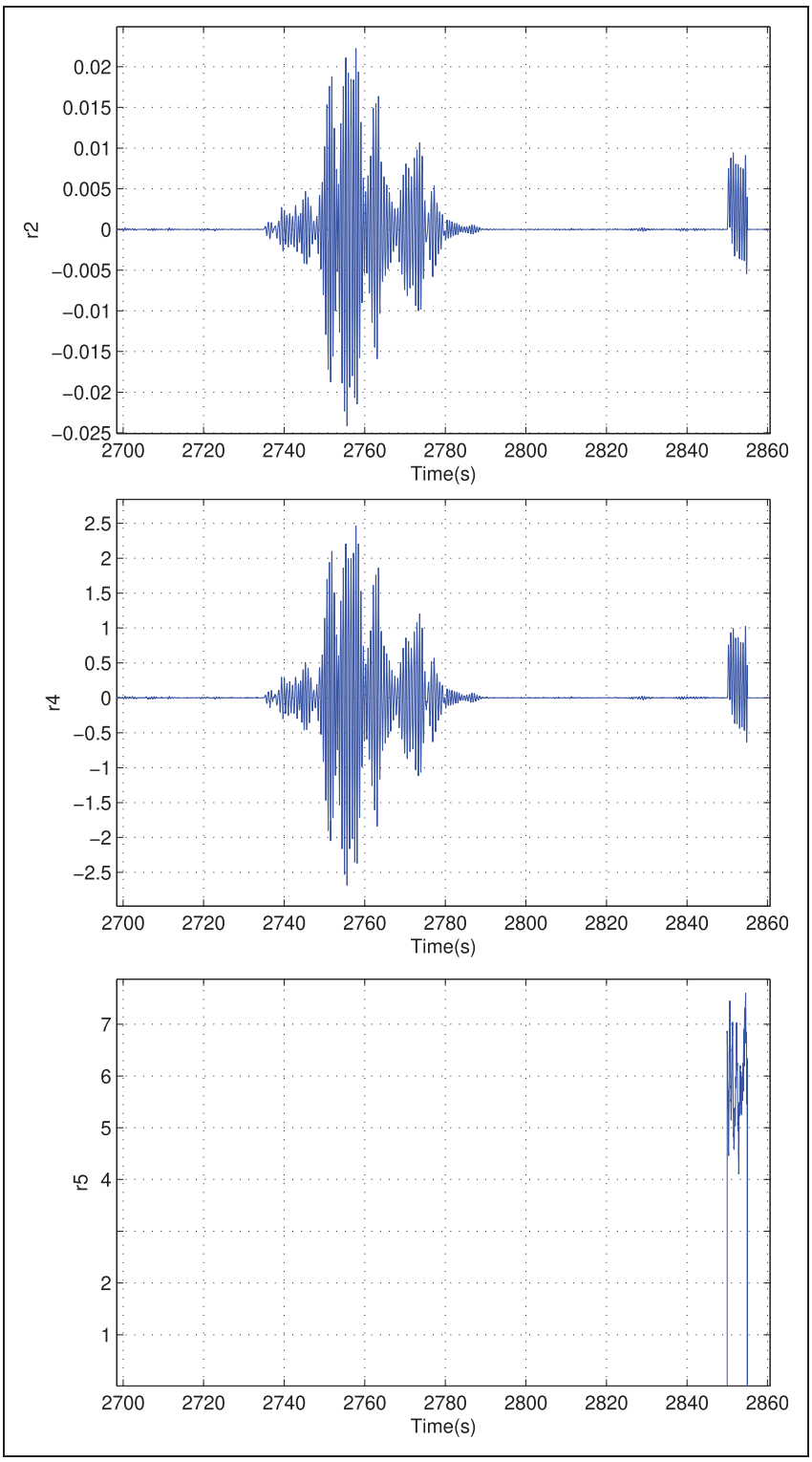

Figure 4. Residual in faulty case.

Then, the virtual actuator can be conceptually designed according to (31) as follows

$$G_a(s) = G_{f^{-1}}(s)G_n(s) = \frac{w_n{}^2(s^2 + 2\hat{\xi}(\mu)\hat{w}_n(\mu)s + \hat{w}_n(\mu)^2)}{\hat{w}_n(\mu)^2(s^2 + 2\xi w_n s + w_n{}^2)} \tag{38}$$

although the design using the LPV model will be done using the state space representation of (5). Then, in case of fault the control signal will be generated as follows:

$$\beta_{ref}^{FTC} = \frac{w_n{}^2(s^2 + 2\hat{\xi}(\mu)\hat{w}_n(\mu)s + \hat{w}_n(\mu)^2)}{\hat{w}_n(\mu)^2(s^2 + 2\xi w_n s + w_n{}^2)}\beta_{ref} \tag{39}$$

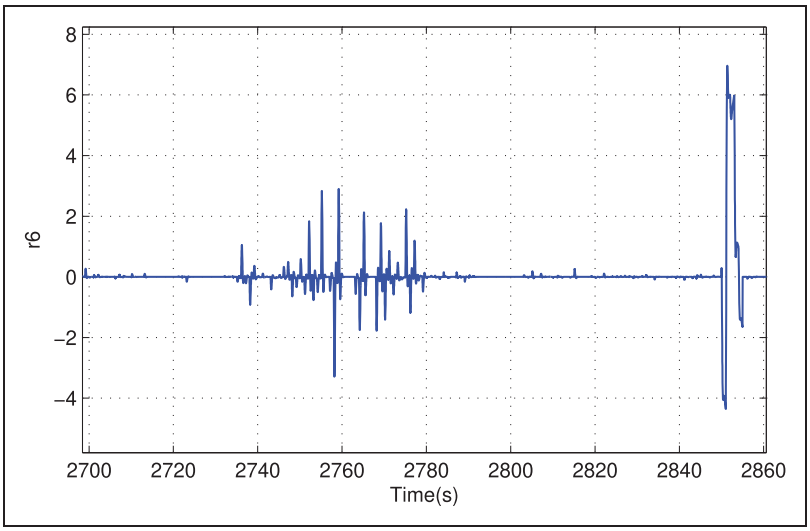

Figure 4. Continued

where $\hat{\xi}(\mu)$ and $\hat{w}_n(\mu)$ are respectively the estimated damping ratio and natural frequency obtained by the application of subspace identification method presented in Section 3.2 using the pressure as scheduling variable and in this case two local models are used.

Sensor fault. In the case of a sensor fault scenario proposed in the wind turbine benchmark,[22] the pitch system input is modified as follows:

$$\beta_{1c} = \beta_{1ref} + \beta_{1f} \tag{40}$$

where

$$\beta_{1f} = \beta_1 - 0.5(\beta_{1m1} + \beta_{1m2}) \tag{41}$$

β_{1ref} is the output of the controller, β_1 is the real pitch angle, β_{1m1} and β_{1m2} are the measured pitch angle with two different sensors.

In the case of the complete loss of the sensor, the measurement issued from the faulty sensor is neglected and it is replaced by the measurement issued from the redundant sensor. In the case of partial sensor fault, the virtual sensor, which compensates the fault, generates a new control signal given by:

$$\beta_{1FTC} = \beta_{1ref} + \beta_{1f} + \Delta\beta_1 = \beta_{1ref} + \beta_1 - \beta_{1m2} \tag{42}$$

then

$$\Delta\beta_1 = 0.5(\beta_{1m1} - \beta_{1m2}) \tag{43}$$

Integration with the FDI scheme. Algorithm 3 summarizes the integration of the FDI and the FTC schemes.

Algorithm 3 FTC algorithm using virtual sensor/actuator

1: Run the system with nominal controller.
2: If an actuator fault is detected and isolated using Algorithm 2, activate the virtual actuator based on (33) after estimating faulty parameters using subspace identification method presented in Section 3.2
3: If a sensor fault is detected and isolated using Algorithm 2, activate the virtual sensor based on (37) after estimating faulty parameters using subspace identification method presented in Section 3.2
3: Run the accommodated system.

Application results

The two fault scenarios already considered for presenting the design of the virtual actuator and sensor are used to illustrate the performance of the proposed AFTC approach:

1. Fault scenario 1: Actuator pitch fault between 2735s and 2780s (case of fault f_8 in Table 2).
2. Fault scenario 2: Sensor pitch fault between 2850s and 2855s (case of fault f_1 in Table 2).

The measured and the estimated pitch angle in these fault scenarios, the residual calculated as difference between the measured and the estimated pitch signal and the fault indicator are presented in Figure 2.

In the faulty system case, using the nominal controller already available in the wind turbine benchmark system, the desired and the real pitch angle

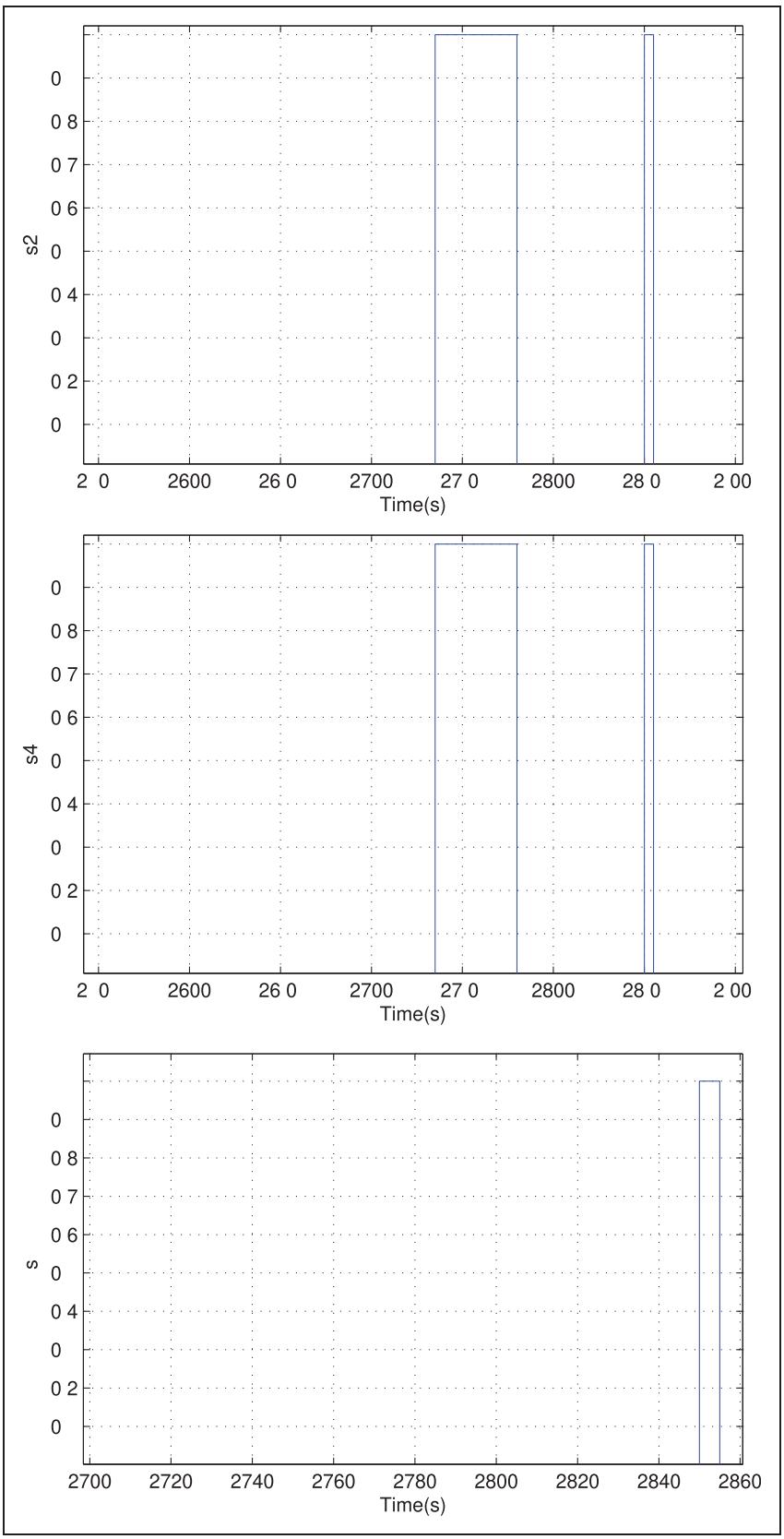

Figure 5. Observed fault signature. (a) Actuator fault indicator (f_8), (b) Sensor fault indicator (f_1).

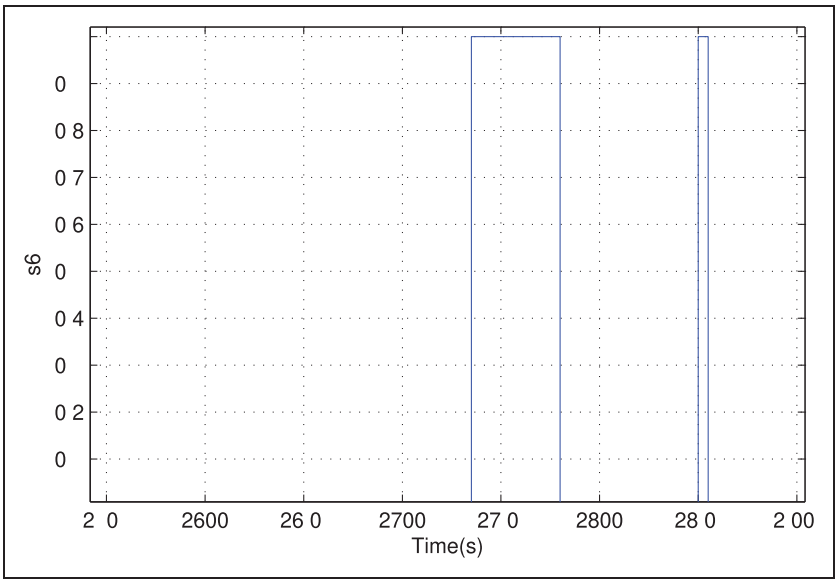

Figure 5. Continued

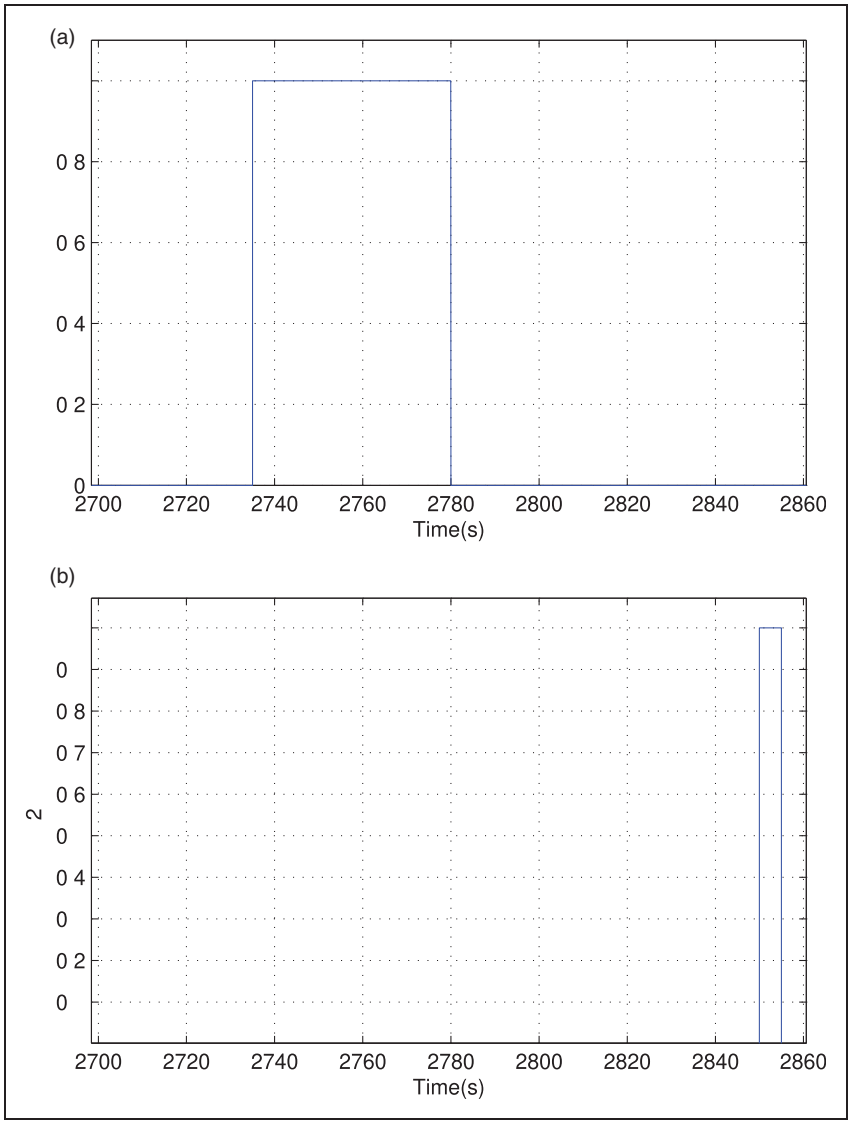

Figure 6. Fault isolation. (a) Damping ratio, (b) Natural frequency

Table 4. Comparison of some fault detection results.

No	Required TD	ATD	TD1	TD2	TD3
F_1	<10Ts	Ts	3Ts	44Ts	6Ts
F_6	<10Ts	Ts	3Ts	22Ts	3Ts
F_7	<3Ts	Ts	3Ts	35Ts	3Ts
F_8	<8Ts	Ts	375Ts	–	2Ts
F_{10}	<50Ts	Ts	3Ts	NC	36Ts

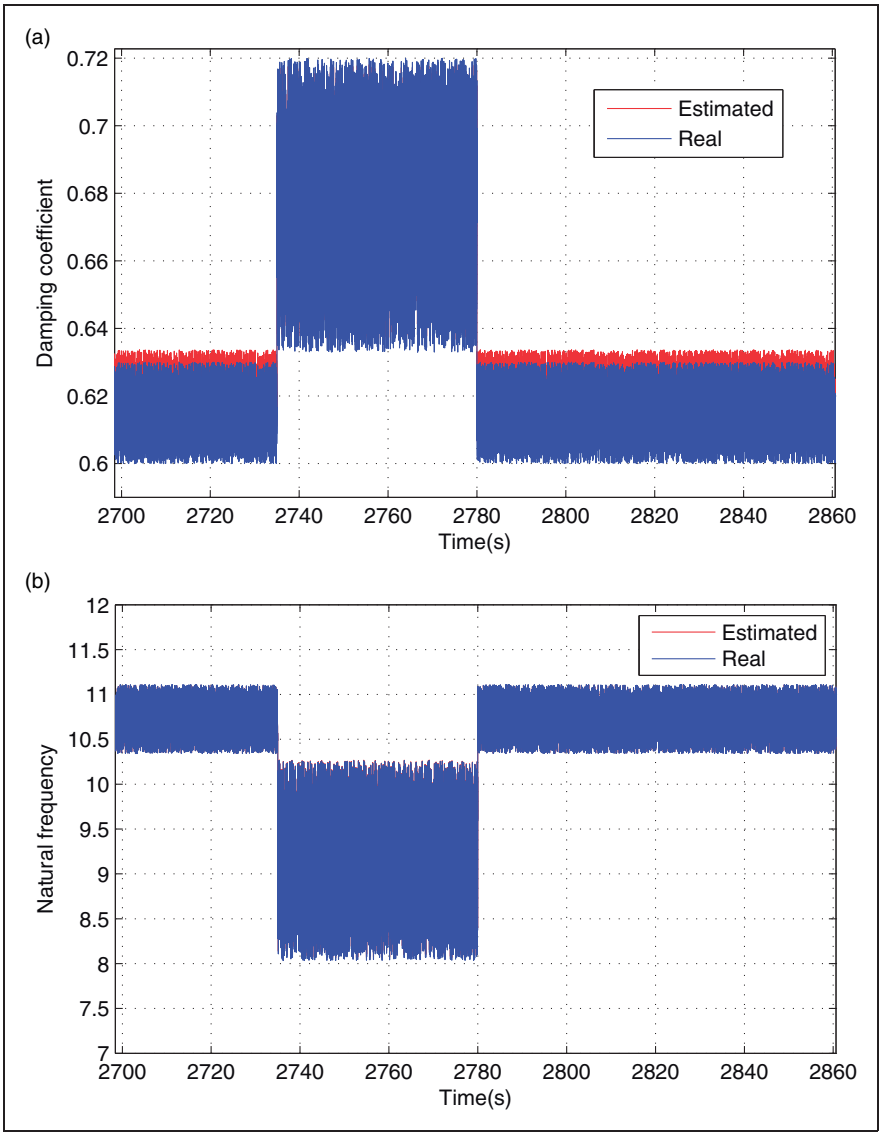

Figure 7. Parameters estimation. (a) Control angle, (b) Pitch angle, (c) Error with FTC.

and the error signal calculated between the two signal are given in Figure 3.

Figure 3 shows that the real pitch angle is far away from the desired one at the time when the fault occurs. To solve this problem a control reconfiguration is required. Using Algorithm 3, the reconfiguration constitutes the activation of virtual sensor or actuator according to the information provided by the FDI module. This FDI procedure requires the residual signal in this case of fault. The activated residuals are presented in Figure 4.

A residual evaluation unit is used to compare the residuals with the threshold to generate the observed fault signature presented in Figure 5 that allows the isolation of the fault using the fault signature matrix corresponding to the previous set of residuals presented in Table 3. The residuals are in rows and the previous fault scenarios in columns.

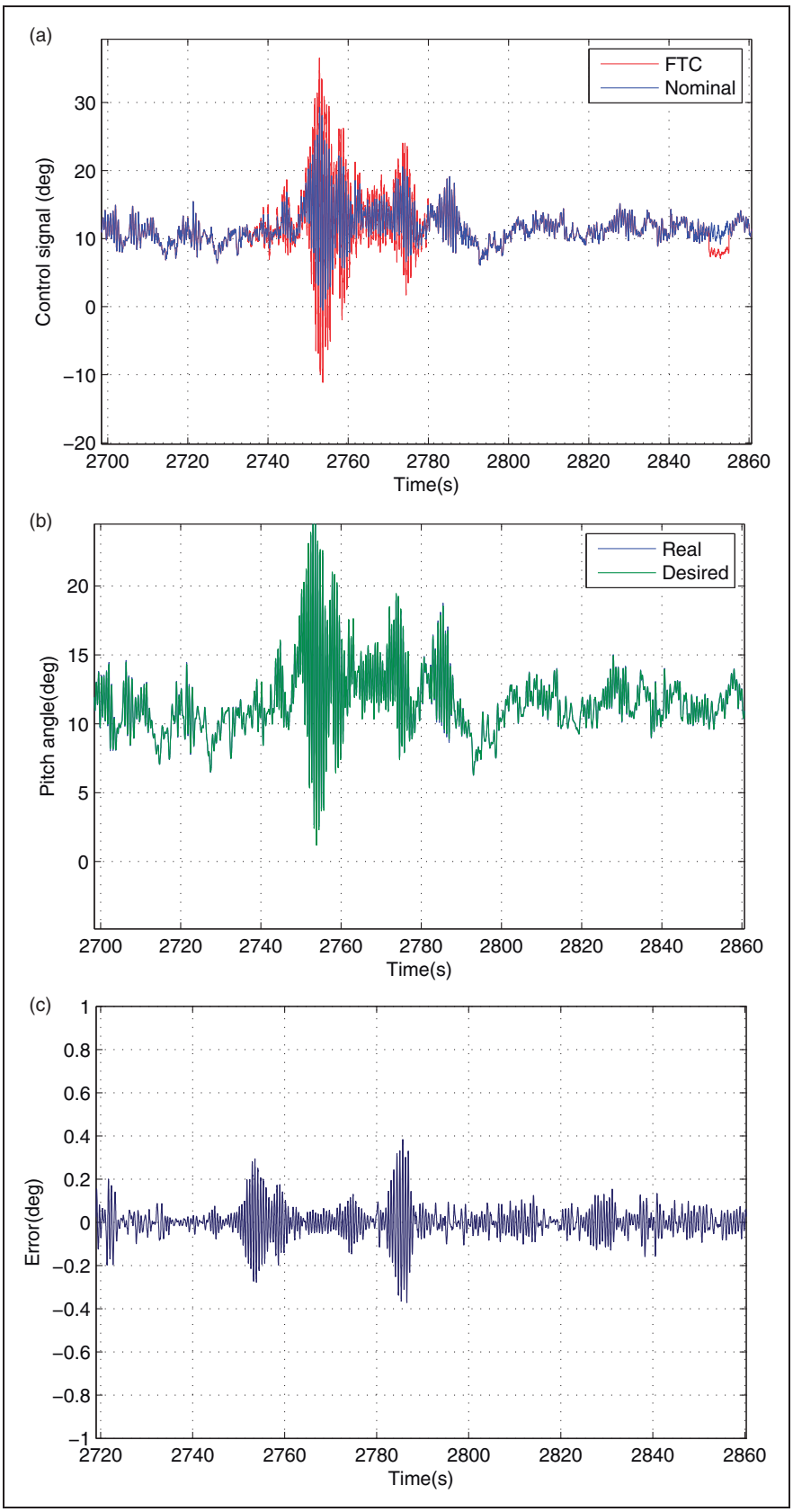

Figure 8. System responses with FTC.

The fault indicators are presented in Figure 6.

The fault tolerance in the actuator fault scenario requires identifying the fault damping ratio and natural frequency. Using the identification approach described in Section 3, these parameters are obtained and presented in Figure 7.

The new FTC signal in this fault scenario, the real and the desired pitch angle and the error between the two pitch angle are presented in Figure 8.

Comparison with other works

The FDI/FTC wind turbine benchmark used in this work is largely treated in the literature as e.g. in literature.[37–39]

- In Sanchez et al.[37] (ATD1), the majority of faults are well detected except the actuator fault that is a change in the pitch system dynamics (f_8). However, this fault is detected using the approach proposed in this paper.
- In Sheibat-Othman et al.[38] (ATD2), only f_1, f_6 and f_7 are detected with a time larger than the required one.
- In Zeng et al.[39] (ATD3), all faults are detected but for example f_1 and f_{10} are detected after a large time period which it is improved using the approach proposed in this paper. This comparison is summarized in Table 4.

In this table *NC* denotes not considered, *ATD* means the time detection with the approach proposed in this work and $TD1, TD2, TD3$ indicate the time detection with the fault detection methods ATD1, ATD2 and ATD3 proposed respectively in literature.[37–39]

Conclusion

In this paper, an integrated FDI/FTC approach for a wind turbine benchmark has been proposed. FDI is based on a robust fault detection approach combined with a subspace LPV estimation algorithm. Fault isolation is based on an algorithm that combines the column/row matching of the observed fault signature with the theoretical ones. FTC is addressed using virtual sensors/actuators and subspace fault identification. Satisfactory results have been obtained for both FDI and the FTC in several fault scenarios proposed in the considered wind turbine benchmark. In the case of the pitch system, an actuator fault which corresponds to dynamic change in the pitch parameters and a sensor fault consisting of a fixed pitch angle value. Future research is focused on the validating of the fault tolerant control procedure of faults using the second wind turbine benchmark that simulates the wind turbine using a high fidelity simulator (FAST).

Declaration of conflicting interests

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