

Fault Diagnosis and Fault Tolerant Control with Application on a Wind Turbine Low Speed Shaft Encoder

Peter Fogh Odgaard* Hector Sanchez** Teresa Escobet**
Vicenc Puig**

* *Section of Automation and Control, Department of Electronic Systems, Aalborg University, Fredrik Bajers Vej 7C, 9220 Aalborg, Denmark; (e-mail:pfo@es.aau.dk)*

** *Automatic Control Department, Technical University of Catalonia (UPC), Rambla Sant Nebridi 22, 08222 Terrassa, Spain; (e-mail:{hector.elay.sanchez, teresa.escobet, vicenc.puig}@upc.edu)*

Abstract:

In recent years, individual pitch control has been developed for wind turbines, with the purpose of reducing blade and tower loads. Such algorithms depend on reliable sensor information. The azimuth angle sensor, which positions the wind turbine rotor in its rotation, is quite important. This sensor has to be correct as blade pitch actions should be different at different azimuth angle as the wind speed varies within the rotor field due to different phenomena. A scheme detecting faults in this sensor has previously been designed for the application of a high end fault diagnosis and fault tolerant control of wind turbines benchmark model. In this paper, the fault diagnosis scheme is improved and integrated with a fault accommodation scheme which enables and disables the individual pitch algorithm based on the fault detection. In this way, the blade and tower loads are not increased to due and individual pitch control algorithm operating with faulty azimuth angle inputs. The proposed approaches is evaluated on the previously mentioned benchmark model, which is based on the FAST aero-elastic code provided by NREL.

1. INTRODUCTION

Wind turbines have become an important source of renewable power generation during the last years. To increase competitiveness, optimize power production and reduce the cost of the produced energy, wind turbine industry is in the process of reducing the materials used for constructing wind turbines and design strategies for controlling the structural loads.

In recent years individual pitch control (IPC) has been developed for wind turbines, with the purpose of reducing blade and tower loads, see for example Bossanyi [2003] and Bossanyi et al. [2013]. Such algorithms depend on reliable sensor information among these is the azimuth angle sensor, which positions the wind turbine rotor in its rotation. These sensor measurements are quite important to have correctly as blade pitch actions should be different for different azimuth angles as the wind speed varies within the rotor field due to different phenomena.

The problem of fault tolerant control (FTC) and fault detection (FD) in wind turbines is still an open issue. A number of benchmark models have been developed to facilitate research in this problem, see Odgaard et al. [2013] and Odgaard and Johnson [2013], the later is based on FAST wind turbine simulator from NREL, USA. One of the faults in the second benchmark model is a fault in the azimuth angle sensor, which is the interest of this paper. An scheme detecting faults within this sensor

has previously been designed Sanchez et al. [2015] and integrated on the previously mentioned benchmark model.

In this paper, the fault diagnosis scheme proposed in Sanchez et al. [2015] is extended and integrated with a fault accommodation scheme which enables and disables the individual pitch algorithm based on the fault detection, such that blade and tower loads are not increased to due and individual pitch control algorithm operating with faulty azimuth angle inputs.

The paper is organized as follows. Section 2 introduces the IPC. Section 3 proposes a diagnosis and fault tolerant schemes for the IPC. Section 4 describes the case study where the proposed approaches are evaluated. Section 5 highlights the concluding remarks and some future research directions.

2. OVERVIEW OF THE PROPOSED APPROACH

2.1 IPC review

The standard baseline industrial wind turbine controller operates in two modes:

- power optimization, in which the blades are kept at their optimal position, and the generator torque is set to keep the wind turbine at the optimal rotational speed, and
- constant power in which the generator torque is kept at its nominal value, and the blade are pitch to

regulate the rotor speed at the nominal value, see Johnson et al. [2006].

The constant power mode, results in a collective pitch reference to all blade pitch actuators. The wind speeds in the rotor fields are non uniform, due to a number of reasons, like turbulence, wind shear, etc. Therefore, it is relevant to adjust the blade pitch angles to mitigate the structural loads induced by these differences in the rotor field to due to the different wind speeds.

The Individual Pitch Controller (IPC) is a scheme proposed to deal with this problem. It is based on computing a component on the pitch reference signals which are non collective, meaning that the each pitch actuator are feed with a pitch reference signals consisting of a sum of the collective pitch reference and the specific reference to the specific pitch actuator computed by the IPC scheme. A conceptual scheme can be seen in Fig. 1. The generator torque controller uses the generator speed and power ω_g and P as inputs, and determines a power reference as output, P_r . The collective pitch controller takes ω_g as input and gives the collective pitch reference β as output. The IPC scheme utilizes the three blade root bending moments τ_{b1} , τ_{b2} and τ_{b3} and the azimuth angle ϕ as inputs, it computes the IPC pitch references β_{b1} , β_{b2} and β_{b3} as output.

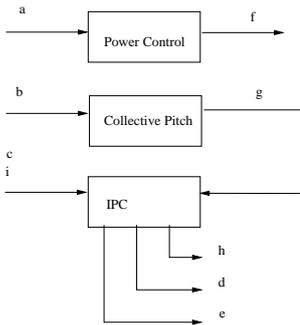


Fig. 1. Illustration of the wind turbine control structure including the IPC scheme.

The IPC scheme has developed for controlling loadings on the wind turbine structures. It can be developed for different oscillation modes of the wind turbine. Typically, it is designed for dealing with the so-called 1P frequency which corresponds to the rotational frequency of the wind turbine, and therefore it is not constant. It uses sensor inputs from the blade root bending moments. The control scheme uses Coleman transformation to transfer these moments from a 3 dimensional rotating coordinate system to a 2 dimensional fixed coordinate system describing the tower moments. In this dimension, PID controllers are used to control the moments such that the computed control signal are subsequently transferred back to the 3 blades. These computed control signals are added onto the collective pitch control signal which is computed for controlling the speed of the wind turbine, see Bossanyi [2003] and Bossanyi et al. [2013]. The following description of the IPC scheme is based on these references. A block diagram of the IPC scheme is illustrated by Fig. 2.1.

The used transformations are defined as given below. From $(\tau_{b1}, \tau_{b2}, \tau_{b3})$ to (τ_1, τ_2) , denoted the Coleman transform.

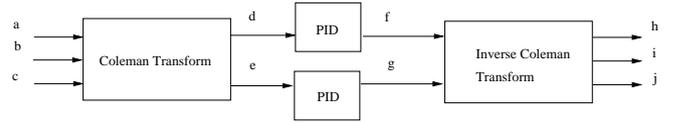


Fig. 2. Illustration of the wind turbine control structure including the IPC scheme.

$$\begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix} = \frac{2}{3} \cdot \begin{bmatrix} \cos(\phi) & \cos(\phi + \frac{2 \cdot \pi}{3}) & \cos(\phi + \frac{4 \cdot \pi}{3}) \\ \sin(\phi) & \sin(\phi + \frac{2 \cdot \pi}{3}) & \sin(\phi + \frac{4 \cdot \pi}{3}) \end{bmatrix} \cdot \begin{bmatrix} \tau_{b1} \\ \tau_{b2} \\ \tau_{b3} \end{bmatrix} \quad (1)$$

Two PID controllers are used to control the values of τ_1 and τ_2 , the computed control signal from these controllers denoted as β_1 and β_2 are subsequently transferred back to the three pitch actuator control signals β_{b1} , β_{b2} and β_{b3} , using the following transformation, which is denoted as the inverse Coleman transformation.

$$\begin{bmatrix} \beta_{b1} \\ \beta_{b2} \\ \beta_{b3} \end{bmatrix} = \begin{bmatrix} \cos(\phi) & \sin(\phi) \\ \cos(\phi + \frac{2 \cdot \pi}{3}) & \sin(\phi + \frac{2 \cdot \pi}{3}) \\ \cos(\phi + \frac{4 \cdot \pi}{3}) & \sin(\phi + \frac{4 \cdot \pi}{3}) \end{bmatrix} \cdot \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} \quad (2)$$

The collective pitch reference computed in order to control the generator speed is added to the individual pitch control signals. (β_{b1} , β_{b2} and β_{b3}).

2.2 Overview of the proposed approach

IPC algorithms depend on reliable sensor information. In particular, the azimuth angle sensor, which positions the wind turbine rotor in its rotation, is quite important to work correctly when used in these algorithms. This is due to the fact that in this control scheme, blade pitch actions are determined using the azimuth angle as the wind speed varies within the rotor field due as described in Section 2.

A model-based scheme for detecting faults in this sensor has previously been designed for the application of a high end fault diagnosis and fault tolerant control of wind turbines benchmark model, see Sanchez et al. [2015]. Here, this fault diagnosis scheme is improved and integrated with a fault accommodation scheme which enables and disables the individual pitch algorithm based on the fault detection. Proceeding in this way, the blade and tower loads are not increased due to an individual pitch control algorithm operating with faulty azimuth angle inputs. The azimuth diagnosis scheme detects faults as bit errors in the binary signal from the encoder. This detection cannot directly be used for fault accommodation as the IPC scheme needs to be able to rely on the azimuth angle and not on/off values. The solution is to feed the detection signal to a new decision function which provides a persistent fault indication signal if a fault (e.g. bit error) has been detected in a window of length L , which in this case is equal one rotation of the rotor. This bit error is modeled by randomly adding an offset to the measurement that corresponds to the bit on which the error is present, Odgaard and Johnson [2013]. In case this decision function provides an active fault indication, the IPC schemes component to the pitch

references are set to 0, as they are based on a faulty azimuth sensor signal.

3. DIAGNOSIS AND FAULT-TOLERANT SCHEME FOR IPC

3.1 Diagnosis scheme for IPC

The diagnosis scheme for detection of faults in the low speed encoder/azimuth angle sensor is based on the approach proposed in Sanchez et al. [2015]. The design of the fault diagnosis system is based on deriving an analytical redundant relation (ARR) which result from combining the model equations with the available sensors for the system. This is the standard procedure to design a fault diagnosis system using model based approaches (for more details see Blanke et al. [2006]).

3.1.1 ARR Generation

ARRs are defined as relations between known variables and can be derived combining the measurement model (known variables) with the system model (unknown variables). Combining the model equations with the available sensors described in the wind turbine benchmark Odgaard and Johnson [2013], by means of the structural analysis approach and perfect matching algorithm [Blanke et al., 2006] using the Satool software [Blanke and Lorentz, 2006], a resulting set of ARRs were obtained in the work of [Sanchez et al., 2015].

From the set of obtained ARRs, the one used in the present work is going to be explained below.

The rotor speed $\omega_{r,m}(t)$ and the azimuth angle $\phi_m(t)$ of the low speed shaft are both known variables. Therefore the ARR (3) can be proposed as a relation between rotor speed and the derivative of the low speed shaft angle $\frac{d\phi_m(t)}{dt}$.

$$\omega_{r,m}(t) = \frac{d\phi_m(t)}{dt} \quad (3)$$

3.1.2 Uncertainty model

The presence of flexible modes in the wind turbine (simulated with aeroelastic FAST simulator) and the modeling errors inherent to the approximation of some model relations lead to the need of using a robust fault detection algorithm able to handle uncertainty Chen and Patton [1999]. One of the most developed families of approaches to deal with model uncertainty, called active, is based on generating residuals, which are insensitive to uncertainty (modeling errors and disturbances), while at the same time sensitive to faults using some decoupling method Chen and Patton [1999]. On the other hand, there is a second family of approaches, called passive, which enhances the robustness of the fault detection system at the decision-making stage using an adaptive threshold Puig et al. [2008].

In this paper, the uncertainty will be located in the parameters bounding their values by intervals using the so-called interval models Puig et al. [2008]. The robustness in fault detection is achieved by means of the passive approach at the decision-making stage using an adaptive threshold generated by considering the set of model responses ob-

tained by varying the uncertain parameters within their intervals.

The residual is generated in order to check the consistency between the observed and the predicted process behavior. The generation of residuals is straightforward in case of static ARRs since they follow directly from the mathematical expressions, as the one used in this paper.

3.1.3 Uncertainty model estimation

One of the key points in passive robust model based fault detection is how models and their uncertainty bounds are obtained. Classical system identification methods are formulated under a statistical framework. Assuming that the measured variables are corrupted by additive noises with known statistical distributions and that the model structure is known, a parameter estimation algorithm will provide nominal values for the parameters together with descriptions of the associated uncertainty in terms of the covariance matrix or confidence regions for a given probability level [Kendall and Alan, 1961], [Dalai et al., 2007]. However, this type of approaches cannot be applied when measurement errors are described as unknown but bounded values and/or modeling errors exist. The problem of bounding the model uncertainty has been mainly stated in many references coming from the robust control field.

Recently, some methodologies that provide a model with its uncertainty have been developed, but always thinking of its application to control [Reinelt et al., 2002]. One of the methodologies assumes the bounded but unknown description of the noise and parametric uncertainty. This methodology is known as *bounded-error* or *set-membership estimation* [Milanese et al., 1996], which produces a set of parameters consistent with the selected model structure and the pre-specified noise bounds.

Uncertainty in the parameters is considered as follows

$$\theta \in \Theta = \{\theta \in \mathbb{R}^{n_\theta} \mid \underline{\theta}_i \leq \theta_i \leq \bar{\theta}_i, i = 1, \dots, n_\theta\} \quad (4)$$

where θ is a vector of uncertain parameters and n_θ is the number of uncertain parameters considered.

Given an input/output static equation expressed as follows:

$$\hat{y}(k, \theta) = g(\theta)u(k) + h(\theta)y(k) \quad (5)$$

where $g(\theta)$ and $h(\theta)$ are uncertain parameters. The goal of the parameter estimation algorithm is to characterize the parameter set Θ (here a box) consistent with the data collected in a fault-free scenario and estimate the output $\hat{y}(k, \theta)$. Given N measurements of system inputs $u(k)$ and outputs $y(k)$ from a scenario free of faults and rich enough from the identifiability point of view, the parameters tolerance α , and a nominal model described by a vector of nominal parameters θ_n obtained using a standard least-square parameter estimation algorithm [Ljung, 1998], the uncertain parameter estimation algorithm proceeds by solving the following optimization problem:

min α

subject to :

$$\begin{aligned} y_i(k) &\in [\underline{\hat{y}}_i(k) - \sigma_i, \bar{\hat{y}}_i(k) + \sigma_i] \quad i = 1, \dots, n_y \quad k = 1, \dots, N \\ \underline{\hat{y}}_i(k) &= \min_{\theta \in \Theta} \hat{y}_i(k, \theta) \quad i = 1, \dots, n_y \quad k = 1, \dots, N \\ \bar{\hat{y}}_i(k) &= \max_{\theta \in \Theta} \hat{y}_i(k, \theta) \quad i = 1, \dots, n_y \quad k = 1, \dots, N \\ \hat{y}(k, \theta) &= G(q^{-1}, \theta)u(k) + H(q^{-1}, \theta)y(k) \quad k = 1, \dots, N \\ \Theta &= [\theta_n(1 - \alpha), \theta_n(1 + \alpha)] \end{aligned} \quad (6)$$

where $\underline{\hat{y}}_i(k)$ and $\bar{\hat{y}}_i(k)$ are the bounds of the system output estimation computed component-wise using the static input/output equation (5) and obtained according to (6), n_y are the number of measurements.

It is assumed that a priori theoretical or practical considerations allow to obtain useful intervals associated to measurement noises, leading to an estimation of the noise bound σ .

The effect of the uncertain parameters θ on the temporal response of the output $\hat{y}(k, \theta)$ will be bounded using an interval satisfying:

$$\hat{y}(k, \theta) \in [\underline{\hat{y}}(k), \bar{\hat{y}}(k)] \quad (7)$$

Such interval can be computed independently for each output $i = 1, \dots, n_y$, neglecting couplings among outputs, as follows:

$$\underline{\hat{y}}_i(k) = \min_{\theta \in \Theta} \hat{y}_i(k, \theta) \quad \text{and} \quad \bar{\hat{y}}_i(k) = \max_{\theta \in \Theta} \hat{y}_i(k, \theta) \quad (8)$$

subject to the equation (5). The optimization problems (8) could be solved using numerical methods as in [Puig et al., 2003] or, more efficiently by means of the zonotope approach presented in [Alamo et al., 2005].

Finally, taking into account that the additive noise in the system is bounded, the following condition should be satisfied

$$y_i(k) \in [\underline{\hat{y}}_i(k) - \sigma_i, \bar{\hat{y}}_i(k) + \sigma_i] \quad i = 1, \dots, n_y \quad (9)$$

in a non-faulty scenario.

The application of the interval-based model to equation (3) is the following:

$$\hat{\omega}_r(t, \theta) = g(\theta) \frac{d\phi_m(t)}{dt} \quad (10)$$

where $\hat{\omega}_r(t, \theta)$ is the estimated rotor velocity function of the azimuth angle derivative $\frac{d\phi_m(t)}{dt}$ (input) and the uncertain parameter $g(\theta)$. Applying the optimization algorithm (6) to equation (10) results in the calculation of α and the estimation of the uncertain parameter $g(\theta)$.

3.1.4 FDI scheme

Fault detection is based on generating a nominal residual comparing the measurements of physical system variables $y(k)$ with their estimation $\hat{y}(k)$ provided by (5):

$$r(k) = y(k) - \hat{y}(k, \theta_n) \quad (11)$$

where $r(k) \in \mathbb{R}^{n_y}$ is the residual set and θ_n the nominal parameters.

When considering model uncertainty located in parameters, the residual generated by (11) will not be zero, even in

a non-faulty scenario. To cope with the parameter uncertainty effect, a passive robust approach based on adaptive thresholding can be used [Puig et al., 2006]. Thus, using this passive approach, the effect of parameter uncertainty in the components $r_i(k)$ of residual $r(k)$ (associated to each system output $y_i(k)$) is bounded by the interval [Puig et al., 2003]:

$$r_i(k) \in [\underline{r}_i(k) - \sigma_i, \bar{r}_i(k) + \sigma_i] \quad i = 1, \dots, n_y \quad (12)$$

where:

$$\underline{r}_i(k) = \underline{\hat{y}}_i(k) - \hat{y}_i(k, \theta_n) \quad \text{and} \quad \bar{r}_i(k) = \bar{\hat{y}}_i(k) - \hat{y}_i(k, \theta_n) \quad (13)$$

Once the uncertainty parameters are estimated and the fault diagnosis is done, the ARR (3) is used to compute a detection signal $\gamma(k)$. This signal is equal 1 if a fault (bit error) is detected at sample k .

Fault isolation consists in identifying the faults affecting the system. It is carried out on the basis of fault signatures, generated after the detection process, and their relation with all the considered faults. Robust residual evaluation presented above allows obtaining a set of observed *fault signatures* $\Gamma(k) = [\gamma_1(k), \gamma_2(k), \dots, \gamma_{n_y}(k)]$, where each fault indicator is given by:

$$\gamma_i(k) = \begin{cases} 0 & \text{if } r_i(k) \in [\underline{r}_i(k) - \sigma_i, \bar{r}_i(k) + \sigma_i] \\ 1 & \text{if } r_i(k) \notin [\underline{r}_i(k) - \sigma_i, \bar{r}_i(k) + \sigma_i] \end{cases} \quad (14)$$

Standard fault isolation reasoning is based on matching the observed fault signature with the so called *Fault Signature Matrix* (FSM), denoted as M . In this matrix, an element $m_{i,j}$ (i indicates rows, j indicates columns) of M is equal to 1 if the fault f^j affects the computation of the residual r_i ; otherwise, the element $m_{i,j}$ is zero-valued. A column of M is known as a *theoretical fault signature* and indicates which residuals are affected by a given fault. For more details see Blanke et al. [2006] and Sanchez et al. [2015] for the application to the wind turbine benchmark problem used in this paper.

3.2 Fault-tolerance scheme for IPC

The next step is to integrate the results of the fault diagnosis scheme with the fault tolerant control scheme as detailed in the following.

A function mapping from $\gamma(k)$ to $\alpha(k)$ is defined.

$$\alpha(k) = \begin{cases} 1 & \text{if } \sum_{i \in k-L \dots k} \gamma(i) > 0, \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

L is set equal to the number of samples found in the time signal of one rotor revolution, covering all errors on all bits.

In case $\alpha(k)$ is equal 1, the IPC pitch reference components are ignored. The new pitch references to each blade $\beta_1, \beta_2, \beta_3$ are given as:

$$\beta_1(k) = \beta(k) + (1 - \alpha) \cdot \beta_{b1}(k), \quad (16)$$

$$\beta_2(k) = \beta(k) + (1 - \alpha) \cdot \beta_{b2}(k), \quad (17)$$

$$\beta_3(k) = \beta(k) + (1 - \alpha) \cdot \beta_{b3}(k) \quad (18)$$

A general scheme showing the integration of the fault diagnosis and fault tolerance for IPC is presented in Fig. 3.

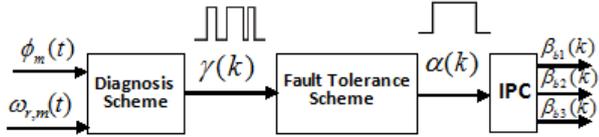


Fig. 3. General Scheme of FD and FTC for IPC

4. CASE STUDY

In this section will be presented some results of the diagnosis and tolerant scheme for the IPC of wind turbines.

4.1 Benchmark Description

This section describes the advanced fault tolerant wind turbine benchmark model Odgaard and Johnson [2013] which is used in this work. The benchmark is based on a wind turbine aeroelastic FAST model, using the 5 MW NREL three bladed variable speed reference wind turbine, developed by NREL for scientific research¹.

The NREL 5 MW model has been used as a reference by research teams throughout the world to standardize baseline offshore wind turbine specifications, and to quantify the benefits of advanced land and sea-based wind energy technologies. The turbine's hub height is 89.6 m and the rotor radius is 63 m with a rated rotor speed is 12.1 rpm while the generator speed is 1200 rpm. The simulator also include baseline controllers that allow to control the three pitch angles, generator and converter torques and yaw position. Different measurements are available from sensors as well as the control references. The sampling period is $T_s = 0.01$ s. In this work an individual pitch controller tuning for the NREL 5 MW reference turbine has been used, see Dunne et al. [2012].

In Figure 4 presents a block diagram of the wind turbine simulation model, provided with the benchmark, including the feedback loops corresponding to the pitch, yaw and torque variables.

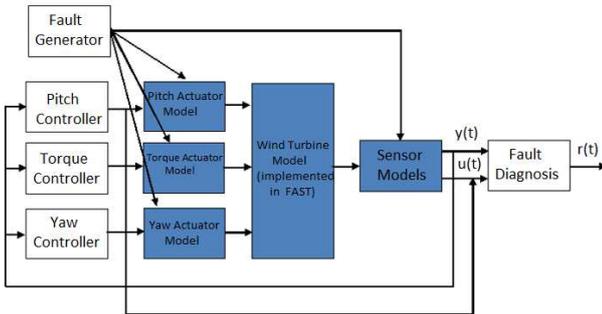


Fig. 4. Block diagram of wind turbine simulation model

According to Odgaard and Johnson [2013], the fault in the azimuth encoder consists of a bit error which is modeled by randomly adding an offset to the measurement that corresponds to the bit on which the error is present. This fault occurs in the time period from 295s to 320s.

¹ <http://www.nrel.gov/docs/fy09osti/38060.pdf>

4.2 Results

In Fig. 5 it can be seen the detection signal resulting from the analytical redundant relation (3) and the function mapping defined in (15). It is observed that a persistent detection signal is obtained, this is useful for integrating the fault diagnosis scheme with the fault tolerant scheme because the new persistent detection signal is used to activate and deactivate the IPC components when the fault is present.

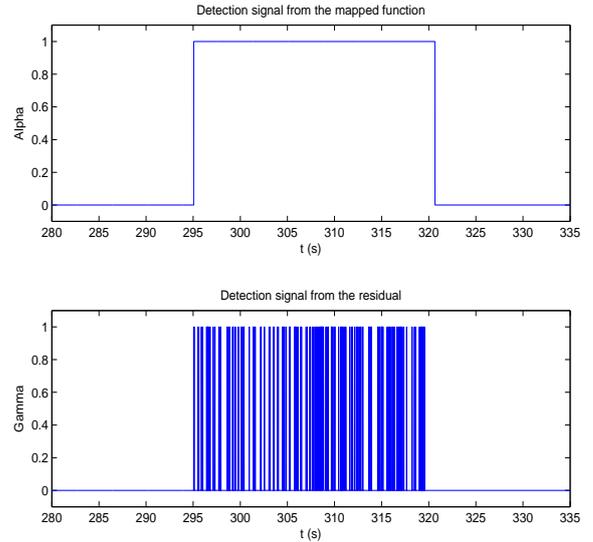


Fig. 5. Detection signal obtained from the ARR and the mapping function

The Fault Tolerant scheme for IPC is shown in Fig. 6, it is observed how the IPC component for blade 1 is deactivated when the fault in the azimuth encoder is present. It is also shown that the tower loads are not increased when the fault is present as a result of the deactivation of the IPC component avoiding that IPC algorithm reads faulty azimuth angle values from the sensor.

5. CONCLUSIONS

In this paper, a diagnosis and fault tolerant schemes for IPC of wind turbines have been proposed. The proposed schemes use the azimuth angle sensor readings, to activate and deactivate the IPC component for the blades in the wind turbine control strategy. The schemes were tested on the FAST aero-elastic code provided by NREL where it was shown that the programmed fault tolerant scheme could achieve a persistent fault detection signal that is useful for the IPC control strategy. The correct detection signal read by the IPC scheme during the presence of the fault allowed the system to deactivate the IPC component during the fault avoiding wrong lectures from the faulty sensor signal and therefore achieving that loads such as the tower ones were not increased.

As a future research work could be proposed to study the scheme presented in this paper with different magnitudes of the fault and also applying different methods for fatigue

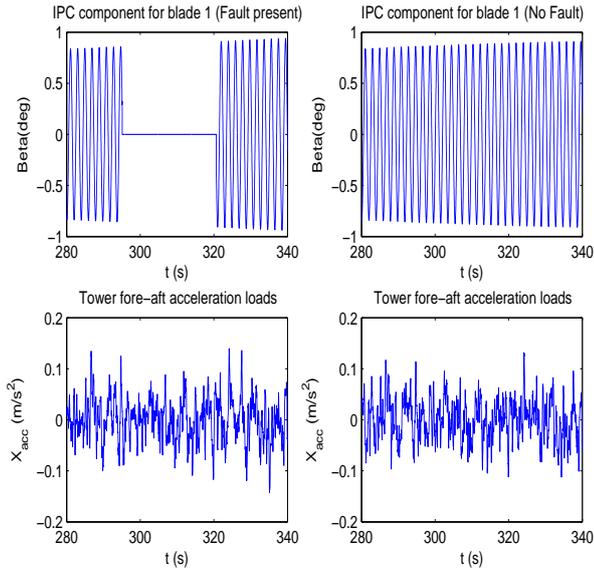


Fig. 6. Fault Tolerant Control scheme for IPC and the tower loads when the scheme is activated and deactivated

estimation integrated with the fault diagnosis and fault tolerant scheme.

REFERENCES

- T. Alamo, J.M. Bravo, and E.F. Camacho. Guaranteed state estimation by zonotopes. *Automatica*, 41(6):1035–1043, 2005.
- M. Blanke and T. Lorentz. SaTool: A software tool for structural analysis of complex automation systems. In *In Proceedings of the 6th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes*, pages 673–678, Beijing, China, 2006.
- M. Blanke, M. Kinnaert, J. Lunze, and M. Staroswiecki. *Diagnosis and Fault-Tolerant Control*. Springer, 2006.
- E.A. Bossanyi. Individual blade pitch control for load reduction. *Wind Energy*, 6:119–128, 2003. doi: DOI: 10.1002/we.76.
- E.A. Bossanyi, P.A. Fleming, and A.D. Wright. Validation of individual pitch control by field tests on two- and three-bladed wind turbines. *IEEE Trans. Control Systems Technology*, 21(4):1067 – 1078, July 2013. doi: 10.1109/TCST.2013.2258345.
- J. Chen and R. J. Patton. *Robust Model-based Fault Diagnosis for Dynamic Systems*. Kluwer Academic Publishers, 1999.
- M. Dalai, E. Weyer, and M.C. Campi. Parameter identification for nonlinear systems: Guaranteed confidence regions through LSCR. *Automatica*, 43(8):1418–1425, 2007.
- F. Dunne, D. Schlipf, L.Y. Pao, A.D. Wright, B. Jonkman, N. Kelley, and E. Simley. Comparison of two independent lidar-based pitch control designs. In *Proc. AIAA Aerospace Sciences Meeting*, Nashville, TN, January 2012.
- K. Johnson, M. Pao, L.Y. Balas, and L. Fingeresh. Control of variable-speed wind turbines - standard and adaptive techniques for maximizing energy capture. *IEEE Control Systems Magazine*, pages 7181, 2006.
- M.G. Kendall and S. Alan. *The advanced theory of statistics*, volume II-III. Hafner, 1961.
- L. Ljung. *System identification*. Springer, 1998.
- M. Milanese, J. Norton, H. Piet-Lahanier, and E. Walter, editors. *Bounding Approaches to System Identification*. Plenum Press, 1996.
- P. Odgaard, J. Stoustrup, and M. Kinnaert. Fault-tolerant control of wind turbines: A benchmark model. *IEEE Transactions on Control Systems Technology*, 21(4): 1168–1182, 2013.
- P.F. Odgaard and K. E. Johnson. Wind turbine fault detection and fault tolerant control - an enhanced benchmark challenge. *Proceedings of the American Control Conference*, pages 4447–4452, 2013.
- P. Puig, A. Stancu, T. Escobet, F. Nejjari, J. Quevedo, and R.J. Patton. Passive robust fault detection using interval observers: Application to the DAMADICS benchmark problem. *Control Engineering Practice*, 14 (6):621–633, 2006.
- V. Puig, J. Saludes, and J. Quevedo. Worst-case simulation of discrete linear time-invariant interval dynamic systems. *Reliable Computing*, pages 251–290, 2003.
- V. Puig, J. Quevedo, T. Escobet, F. Nejjari, and S. de las Heras. Passive Robust Fault Detection of Dynamic Processes using Interval Models. *IEEE Transactions on Control Systems Technology*, 16:1083–1089, 2008.
- W. Reinelt, A. Garulli, and L. Ljung. Comparing different approaches to model error modeling in robust identification. *Automatica*, 38(5):787–803, 2002.
- H.E. Sanchez, T. Escobet, V. Puig, and P.F. Odgaard. Fault diagnosis of advanced wind turbine benchmark using interval-based ARRs and observers. *IEEE Transaction on Industrial Electronics*, 2015. Accepted for publication.