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Robust Fault Diagnosis for a Horizontal Axis Wind Turbine

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Abstract: This paper presents an H_∞ optimization-based approach for the detection and isolation of faults in a horizontal axis wind turbine. The primary residuals are generated from separate parity equations for each of the blade pitch and drivetrain subsystems. Then, a robust secondary residual filtering scheme is developed to remove undesirable cross coupling in fault-residual pairings while suppressing the effects of the strong nonlinearity of the aerodynamic rotor torque-speed relationships, the effects of unmodelled dynamics and noise. Solutions are obtained using H_∞ and μ-synthesis tools. Sensor, actuator and system/parameter faults are diagnosed using specified information about the nature of the faults as well as sensor redundancy. Results are included demonstrating the diagnosis of individual faults specified with the benchmark model for wind turbine fault detection and isolation.

Keywords: Fault detection and isolation, H-infinity, Turbines

1. INTRODUCTION

Wind turbines are attracting increasing attention as viable alternatives for renewable energy generation. The wind resource itself is quite abundant, cheap and free of greenhouse gas emissions. However, wind turbines (WT) expensive to install, operate and maintain. To justify their very high installation and maintenance costs, the trend over the last couple of decades has been to build ever larger wind turbines with high outputs. Today turbines that generate 5-6 MW or more are in development or are being installed. To avoid objections to the aesthetic and land use issues and noise emissions from onshore WT installations, more and more new developments target less accessible, offshore installations (Hau, 2006). This increases the cost per failure. To ensure reliability and reduce downtimes for these installations, carefully designed fault diagnosis and fault tolerant control systems play a very critical role. The timely detection, isolation and accommodation of faults coming from various sensors and actuators or from system/subsystem deterioration are crucial for the cost effective operation of the wind turbines and their subsequent commercial success in the energy market.

A review of the few existing works on fault diagnosis and fault tolerant control of wind turbines has been given in Esbensen and Sloth (2009). An observer based scheme was described in Wei et al (2008) for estimating pitch sensor faults. Odgaard et al (2009a) describe an unknown input observer for the detection of sensor faults in the drivetrain of a three-blade horizontal axis wind turbine (HAWT). Donders (2002) proposed the use of a discrete time Kalman filter and an Interacting Multiple-Model estimator for the detection and estimation of unknown actuator gains in a HAWT.

This paper deals with fault diagnosis (detection and isolation) of a HAWT using a model-based framework that encompasses both the blade pitch subsystems, the drivetrain subsystems, and the generator/converter subsystem. In the proposed approach, primary residuals are first generated from a parity equation approach and then passed onto a robust secondary residual generation or filtering scheme. The robust scheme attempts to remove undesirable cross-coupling between fault-residual pairs and accommodates the strong aerodynamic nonlinearities and modelling uncertainties. Solutions for the robust schemes are obtained using H_∞ and μ-synthesis tools from linear robust control theory.

2. SYSTEM DESCRIPTION

2.1 Overview of the System

The three-blade horizontal axis wind turbine comprises of the components depicted in the schematic of Fig.1. This is the typical layout adopted for the Benchmark WT FDI Problem (Odgaard, et al. 2009b). Figure 1 also shows the torque-speed physical causality for the interconnection between the subsystems and the sensor measurements available for the controller. The set up includes two pitch angle sensors for each blade, two speed sensors for each of the rotor and the generator, and sensors for generator power and torque. The controller acts by providing a reference pitch angle for the pitch system and a reference torque for the converter which in turn regulates the generator torque. The workings of the system are described in further detail in Johnson et al (2006) and in Esbensen and Sloth (2009). In this work, the particular structure of the control system summarized in Odgaard et al (2009b) will be used without change.

2.2 System Models

Pitch and Blade Systems: Each of the blade pitch systems (with their blade pitching actuators) are modelled as

$$\beta_i(s) = T(s)\beta_e = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2}(\beta_r + \beta_{i,fbk}) \qquad (1)$$

For the Benchmark problem, the following construction of the feedback signal based on the two pitch angle sensors (per blade) has been adopted:

$$\beta_{i,fbk} = \beta_i - \frac{1}{2}(\beta_{i,m1} + \beta_{i,m2}) \quad (2)$$

where, β_i is the actual pitch angle. It turns out that this construction introduces a cross coupling been pitch angle sensor faults as will be shown below.

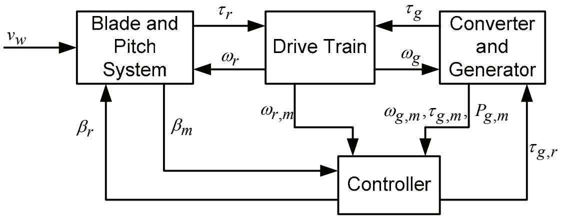


Fig. 1. Overview of the wind turbine system (Sensor measurements are designated with the subscript *m*.).

The aerodynamic rotor torque is modelled by:

$$\tau_r(t) = \sum_{1\le i\le 3} \frac{\rho \pi R^3 C_q(\lambda(t), \beta_i(t)) v(t)_w^2}{2} \quad (3)$$

where, $\lambda = \omega_r R / v_w$ is the tip speed ratio and $C_q(\lambda(t), \beta_i(t))$ is the torque coefficient table (as given in, say, Johnson et al(2006)). This represents a major nonlinearity in the WT system and is one of the key considerations in the diagnostic approach discussed below.

Drivetrain System: A two mass (rotor-generator) model of the drivetrain has the following state space description (Odgaard et al(2009b))

$$\begin{bmatrix} \dot{\omega}_r(t) \\ \dot{\omega}_g(t) \\ \dot{\theta}_\Delta(t) \end{bmatrix} = A \begin{bmatrix} \omega_r(t) \\ \omega_g(t) \\ \theta_\Delta(t) \end{bmatrix} + B \begin{bmatrix} \tau_r(t) \\ \tau_g(t) \end{bmatrix} \quad (4)$$

$$A = \begin{bmatrix} -\frac{B_{dt} - B_r}{J_r} & \frac{B_{dt}}{N_g J_r} & \frac{-K_{dt}}{J_r} \\ \frac{\eta B_{dt}}{N_g J_g} & \frac{-\eta B_{dt}}{N_g^2 J_g} - \frac{B_g}{J_g} & \frac{\eta K_{dt}}{N_g J_g} \\ 1 & \frac{-1}{N_g} & 0 \end{bmatrix} \quad B = \begin{bmatrix} \frac{1}{J_r} & 0 \\ 0 & \frac{-1}{J_g} \\ 0 & 0 \end{bmatrix}$$

where B_{dt}, B_r and B_g are torsional damping/viscous friction coefficients of the drivetrain, rotor and generator, respectively; N_g is the gear ratio; J_r and J_g are the rotor and generator inertia; K_{dt} is the torsional stiffness of the drivetrain and η is the drivetrain efficiency. The model gives the evolution of the rotor speed(ω_r) and generator speed (ω_g).

Generator and Converter: A first order dynamics is assumed for the convertor:

$$\frac{\tau_g(s)}{\tau_{g,r}(s)} = T_g(s) = \frac{\alpha_{gc}}{s + \alpha_{gc}} \quad (5)$$

And the power of the generator is given by:

$$P_g(t) = \eta_g \omega_g(t) \tau_g(t) \quad (6)$$

3. DIAGNOSTIC SCHEME

The proposed approach for fault diagnostics in the HAWT is based on the use of a parity equation method to create primary residuals. Then, the a diagnostic scheme design that is robust with respect to disturbances, unmodeled dynamics, and nonlinear aerodynamics, is obtained by generating secondary residuals via a robust H_∞ filtering method (detailed in Section 4). For both steps, it is sought to make the diagnostic scheme for the pitch subsystems to be independent of that for the drivetrain subsystem.

3.1 Residual Generation for the Pitch Subsystems

The diagnostic scheme for the three blade pitch subsystems is depicted in Fig. 2. This scheme allows detecting and isolating faults in the pitch sensors as well as dynamic faults in each of the pitch subsystems. The scheme is capable of isolating multiple faults that are not occurring within the same pitch subsystem.

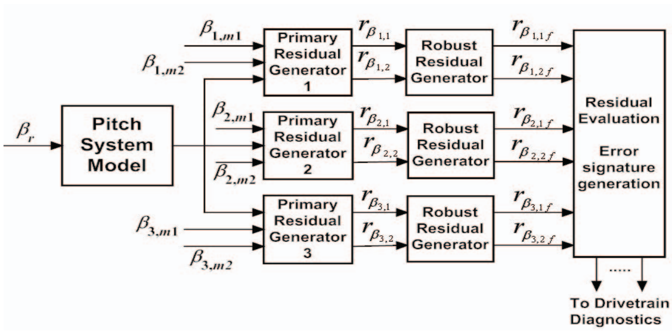


Fig 2. Diagnostic scheme for the three pitch subsystems.

In the presence of (sensor or system) faults, the pitch system model in (1) can be used to generate an estimate of the pitch angles from the pitch reference input, which is assumed to be available. The two sensor measurement of the pitch angles are then:

$$\begin{aligned} \beta_{m1}(s) &= T(s)(\beta_r + \beta_{fbk}) + \Delta T(s, \Delta\beta_\zeta, \Delta\beta_{\omega_n})(\beta_r + \beta_{fbk}) + \Delta\beta_{m1} \\ \beta_{m2}(s) &= T(s)(\beta_r + \beta_{fbk}) + \Delta T(s, \Delta\beta_\zeta, \Delta\beta_{\omega_n})(\beta_r + \beta_{fbk}) + \Delta\beta_{m2} \end{aligned} \quad (7)$$

where β_{m1}, β_{m2} are the sensor measurements of the pitch angles, $\Delta\beta_{m1}, \Delta\beta_{m2}$ are sensor faults, and $\Delta\beta_\zeta, \Delta\beta_{\omega_n}$ represent the pitch system faults (due to hydraulic pressure drop or air content). Two residuals for each pitch system can then be defined as $r_{\beta_1} = \beta_{m1} - \hat{\beta},\ r_{\beta_2} = \beta_{m2} - \hat{\beta}$, where $\hat{\beta} = T(s)\beta_r$. Using (1), (2) and (8), after some manipulations, the explicit dependence of the residual on the faults can be expressed as:

$$\begin{aligned} r_{\beta_1} &= \left(1 - \frac{T(s)}{2}\right)\Delta\beta_{m1} - \frac{T(s)}{2}\Delta\beta_{m2} + \Delta T(s, \Delta\beta_\zeta, \Delta\beta_{\omega_n})\beta_r \\ r_{\beta_2} &= \left(1 - \frac{T(s)}{2}\right)\Delta\beta_{m2} - \frac{T(s)}{2}\Delta\beta_{m1} + \Delta T(s, \Delta\beta_\zeta, \Delta\beta_{\omega_n})\beta_r \end{aligned} \quad (8)$$

This shows a cross-coupling in the sensor fault-residual pairing. Ideally, we would like to have the first residual affected only by $\Delta\beta_{m1}$ and the second residual affected only by $\Delta\beta_{m2}$. One objective of the robust residual generator (to be discussed in Section 4) is to obtain a good degree of decoupling for the purposes of fault isolation. Both residuals would of course be affected by the parametric/system faults.

After secondary filtering (with the robust filter), the residuals are sent to a residual evaluation unit where they are compared with fixed thresholds to generate an error signature and to detect and isolate the presence of faults.

3.2 Residual Generation for the Drivetrain Subsystem

The proposed diagnostic scheme for the drivetrain system is shown in Fig. 3. It assumes that wind velocity v_w is available (from wind speed estimators, see for e.g., Ostergaard, et al, 2007) and that the sensor measuring the generator torque ($\tau_{g,m}$) is fault free. The scheme generates two estimates of the rotor aerodynamic torque $\tau_{r,1}$ and $\tau_{r,2}$ using sensor signals $\omega_{r,m1}$ and $\omega_{r,m2}$, respectively, and utilizing the error signature from the pitch subsystem diagnostics to select the pitch angle sensors that are not faulty. The estimated torque values are then used in a drivetrain model to generate rotor and generator speed estimates ($\hat{\omega}_{r,1}, \hat{\omega}_{g,1}$), ($\hat{\omega}_{r,2}, \hat{\omega}_{g,2}$). In presence of faults, from the model equations of the drivetrain subsystem (4), we can write:

$$\begin{bmatrix} \omega_{r,i}(s) \\ \omega_{g,i}(s) \end{bmatrix} = T_{rg}(s) \begin{bmatrix} \tau_r(s) \\ \tau_g(s) \end{bmatrix} + \Delta T_{rg}(s, \Delta\eta) \begin{bmatrix} \tau_r(s) \\ \tau_g(s) \end{bmatrix} + T_{rg}(s) \begin{bmatrix} 0 \\ \Delta\tau_g(s) \end{bmatrix} + \begin{bmatrix} \Delta\omega_{r,i}(s) \\ \Delta\omega_{g,i}(s) \end{bmatrix} \quad i = 1,2 \tag{9}$$

where T_{rg} is the transfer function matrix for the system in (4), $\Delta\tau_g$ is the torque generator fault, $\Delta\omega_{r,i}, \Delta\omega_{g,i}$ are the rotor and generator speed sensor faults, and $\Delta\eta$ (drop in efficiency) is the system/parametric fault. The estimated rotor and generator speeds according to the scheme in Fig. 3 are given by:

$$\begin{bmatrix} \hat{\omega}_{r,i}(s) \\ \hat{\omega}_{g,i}(s) \end{bmatrix} = T_{rg}(s) \begin{bmatrix} \hat{\tau}_{r,i}(s) \\ \tau_g(s) \end{bmatrix} + T_{rg}(s) \begin{bmatrix} 0 \\ \Delta\tau_g(s) \end{bmatrix} \quad i = 1,2 \tag{10}$$

where, the rotor torque estimate is used here for lack of its measurement. It is obtained from the relationship in (3) as:

$$\hat{\tau}_{r,i} = F(\omega_{r,i} + \Delta\omega_{r,i}) \simeq \tau_r + \chi\Delta\omega_{r,i} \tag{11}$$

where χ is a torque-speed gradient function from the local linearization of the function F, which is shorthand for the nonlinear aerodynamic rotor torque-speed relationship referred to in equation (3). By defining the four primary residuals as:

$$\begin{aligned} r_{\omega_{r1}} &= \omega_{r,m1} - \hat{\omega}_{r,1} & r_{\omega_{g1}} &= \omega_{g,m1} - \hat{\omega}_{g,1} \\ r_{\omega_{r2}} &= \omega_{r,m2} - \hat{\omega}_{r,2} & r_{\omega_{g2}} &= \omega_{g,m2} - \hat{\omega}_{g,2} \end{aligned} \tag{12}$$

After some manipulations of (9) and (10), and using (11), the residual dynamics as function of the faults can be written as:

$$\begin{aligned} r_{\omega_{r1}} &= (1 - T_{\omega_r\tau_r}(s)\chi)\Delta\omega_{r1} + \Delta T_{rg1}(s, \Delta\eta) \begin{bmatrix} \tau_r(s) \\ \tau_g(s) \end{bmatrix} \\ r_{\omega_{g1}} &= -T_{\omega_g\tau_r}(s)\chi\Delta\omega_{r1} + \Delta\omega_{g1} + \Delta T_{rg2}(s, \Delta\eta) \begin{bmatrix} \tau_r(s) \\ \tau_g(s) \end{bmatrix} \end{aligned} \tag{13}$$

This structure of the primary residuals allows us to set the objective of the robust residual generator (to be detailed in Section 4) as one of suppressing the effects of all faults and disturbances except $\Delta\omega_{r1}$ (rotor speed sensor faults).

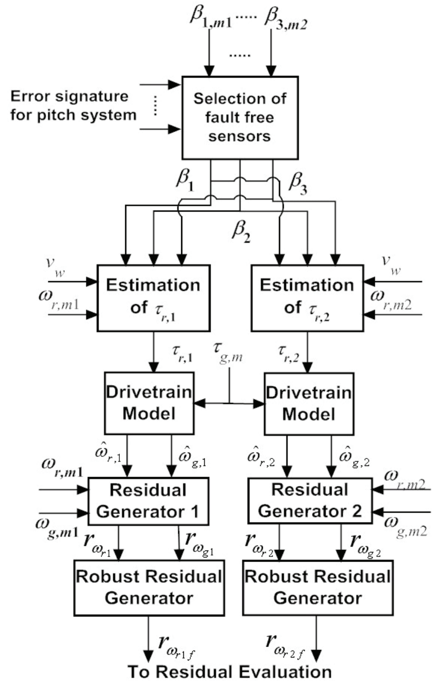


Fig. 3. Diagnostic scheme for drivetrain subsystem.

For detecting faults in the generator speed sensors, other information available from the power/torque sensors gives a more direct route (See (14) below).

Again, post filtering, the residuals are sent to a residual evaluation unit where they are compared with fixed thresholds where they are assigned an error signature that will be used to detect and isolate the faults.

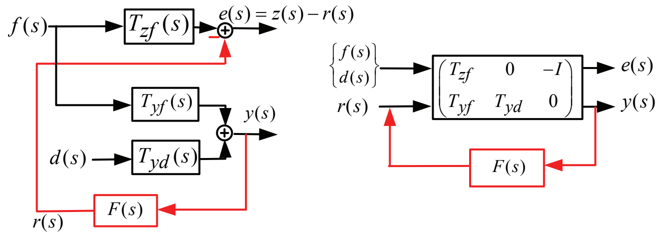
3.3 Residual Generation for the Generator/Convertor Subsystem

The residuals for the generator/convertor subsystem are obtained by using the measured generator torque and power. The residual for the detection and isolation of the torque sensor fault $\Delta\tau_g$ is defined as $r_{\tau_g} = \tau_{g,m} - \hat{\tau}_g$, with $\hat{\tau}_g = T_g(s)\tau_{g,ref}$. For the detection and isolation of the faults in the generator speed sensors, the following residuals are constructed:

$$r_{\omega_g Pi} = \omega_{g,mi} - \frac{P_{g,m}}{\tau_{g,m}} \quad i = 1,2 \tag{14}$$

4. ROBUST RESIDUAL GENERATION

The method for the generation of secondary residuals for the WT system we describe in this section utilizes results from robust control theory (Blanke, et al, 2003). Suppose *y* denotes the primary residual vector generated through the parity equations described above, *f* denotes the fault vector, *d* denotes the disturbance vector and *z* denotes a signal constructed to have the characteristics of the desired residual through a choice of a transfer function T_{zf} (s). The following interconnection depicts the formulation of the robust residual generation scheme.



a) Abstraction for robust residual generation b) Standard form

Fig. 4. Frame work for robust residual generation (Blanke, et. al, 2003).

The main goal is to design a filter F(s) that, when applied on the primary residual vector, will replicate the characteristics specified on the fault vector through T_{zf}(s) as close as possible, while at the same time rejecting the influence of the disturbances. Note that $T_{zd}(s)=0$ is already selected in this formulation. This goal can be cast into a standard H_∞ (or H_2) optimization problem as shown in Fig. 4.

4.1 Pitch Subsystems

For each blade's pitch control system, the four possible faults (2 sensor faults and two system/parametric faults) can be addressed simultaneously. To this end, introduce the following notations.

$$y=\begin{bmatrix} r_{\beta_1} & r_{\beta_2} \end{bmatrix}^T \qquad f=\begin{bmatrix} \Delta\beta_{m1} & \Delta\beta_{m2} & \Delta\beta_{\omega_n} & \Delta\beta_{\zeta} \end{bmatrix}^T \quad (15)$$

Starting from the primary residual generator (parity equation (8)) and considering linearization of the transfer $T(s)$ (1) with respect to parametric faults in ζ and ω_n , the fault to residual transfer function matrix $T_{yf}(s)$ can be shown to be given by:

$$T_{yf}(s)=\begin{bmatrix} 1-\dfrac{T(s)}{2} & -\dfrac{T(s)}{2} & T_1(s) & T_2(s) \\ -\dfrac{T(s)}{2} & 1-\dfrac{T(s)}{2} & T_1(s) & T_2(s) \end{bmatrix} \qquad (16)$$

where

$$T_1(s)=\frac{s(2\omega_n s+2\omega_n^2\zeta)}{(s^2+2\zeta\omega_n s+\omega_n^2)^2}\bar{\beta}_r \text{ and } T_2(s)=\frac{-2\omega_n^3 s}{(s^2+2\zeta\omega_n s+\omega_n^2)^2}\bar{\beta}_r .$$

Here, $\bar{\beta}_r$ is a nominal reference pitch angle. Model uncertainty and neglected terms from the linearization (perturbations of the original pitch actuator transfer function T(s)) as well as sensor noise components can be modelled (perhaps conservatively) through the following high pass form for the disturbance to residual transfer matrix:

$$T_{yd}(s)=k\frac{s+z_1}{s+p_1}\begin{bmatrix}1\\1\end{bmatrix} \qquad (17)$$

Considering that a low pass filter is desirable for suppressing noise, and that the filter should be causal (relative degree>0), the specification T_{zf}(s) can be chosen as follows:

$$T_{zf}(s)=\begin{bmatrix} \dfrac{\alpha_1}{s+\alpha_1} & 0 & \dfrac{\alpha_3^3}{(s+\alpha_3)^3} & \dfrac{\alpha_4^4}{(s+\alpha_4)^4} \\ 0 & \dfrac{\alpha_1}{s+\alpha_1} & \dfrac{\alpha_3^3}{(s+\alpha_3)^3} & \dfrac{\alpha_4^4}{(s+\alpha_4)^4} \end{bmatrix} \qquad (18)$$

The constants α_1, α_3, and α_4 can be selected to meet detection time specifications for the various sensor and dynamic faults.

For the specific wind turbine pitch system model considered here, the transfer function matrix T_{yf}(s) contains transmission zeros at zero. To suppress their effects, an integral action is included in the filter by augmenting (multiplying) the transfer functions in (16) and (17) (or the system matrix in the standard form) with integrators. This approach requires a bilinear transformation to move the $-j\omega$ axis poles so introduced before H_∞ methods could be applied. Once the filter is solved for in the transformed complex domain, the inverse bilinear transformation is applied to obtain the filter in the original complex domain. Finally, the integrator is appended to the filter before connecting it in the original diagnostic scheme for the pitch system. The designed filter should address the coupling between the sensor faults introduced due to the feedback of sensor outputs in the pitch control system. Users can adjust this decoupling in the frequency range of interest by defining the matrix transfer function T_{zf}(s) accordingly or appending frequency dependent performance weights (Skogestad and Postlethwaite, 2005).

The filtered residuals obtained with the above procedure were then analyzed and suitable thresholds were selected to categorize the fault signatures as 0 (no fault detected) and 1 (fault detected). The following table summarizes the detection and isolation scenario for each blade pitch system.

Table.1 Fault Signatures for Pitch Subsystem (per blade)

		Residuals	
	Faults	$r_{\beta 1}$	$r_{\beta 2}$
Sensor Faults	$\Delta\beta_{m1}$	1	0
	$\Delta\beta_{m2}$	0	1
System Faults	ω_n,ζ	1	1

4.2 Drivetrain Subsystem

For the drivetrain subsystem, the robust residual filtering scheme is developed by paying special attention to the nonlinear functional relationships between the rotor torque and rotor speed. Selecting a pairing between the first rotor speed sensor and the first generator speed sensor, the corresponding residual and fault vectors are given by:

$$y=\begin{bmatrix} r_{\omega_{r1}} & r_{\omega_{g1}} \end{bmatrix}^T \qquad f=\begin{bmatrix} \Delta\omega_{r1} & \Delta\omega_{g1} & \Delta\eta \end{bmatrix}^T \qquad (18)$$

The last element of the fault vector represents the system faults due to a drop in the efficiency η. The fault to residual transfer function is given by:

$$T_{yf}(s)=\begin{bmatrix} 1-T_{\omega_r\tau_r}(s)\chi & 0 & T_{\omega_r\eta} \\ -T_{\omega_g\tau_r}(s)\chi & 1 & T_{\omega_g\eta} \end{bmatrix} \qquad (19)$$

Here, $T_{\omega_r\tau_r}(s)$ and $T_{\omega_g\tau_r}(s)$ are the nominal system transfer functions from the original drivetrain model (4). χ is a torque-speed gradient function from the local linearization of the nonlinear rotor torque-speed relationship (3).

The variation of the torque/power coefficient with changing operating points of the wind turbine can be considered to lead to a modelling uncertainty in the computation of χ. To this end, numerical (dynamic) system identification experiments were conducted using MATLAB's System Identification Toolbox (**ident**) to determine the range of the variation in χ. It was found that a low pass transfer function with a large break frequency λ and an uncertain gain K is found to cover the variation in χ for a range of operating points of the wind turbine. This allows us to describe the resulting transfer matrix as an uncertain LTI object with explicit bounds on the uncertainty.

$$\chi(s) = K\lambda/(s+\lambda), \qquad K \in [-1.5, \;\; 7]\times 10^5 \tag{20}$$

The sign of K changes at high rotor speeds consistent with the negative gradient of the power coefficient (see, for e.g., Johnson et al 2006).

Recall that the rotor torque used in the residual generation model results in a coupling between the fault in the generator speed sensor and the residual for the rotor speed. Since a separate scheme is outlined for detecting faults in the generator speed from available generator torque and power measurements, we focus on using the structure $T_{yf}(s)$ above for detecting faults in the rotor speed sensor (and the system faults due to a drop in the efficiency) while decoupling it from the fault in the generator speed sensor. This is the consideration in the specification of $T_{zf}(s)$ as given below.

The transfer functions from the system fault ($\Delta\eta$) to the residuals are obtained by considering the perturbation of the original state space drivetrain model with respect to the efficiency η, at various nominal operating points corresponding to the nominal inputs $\bar{\tau}_r$ and $\bar{\tau}_g$. After some matrix perturbation computations, one arrives at the following (Bernstein, 2005):

$$\begin{bmatrix} T_{\omega_r\eta}(s) \\ T_{\omega_g\eta}(s) \end{bmatrix} = C(sI-A)^{-1}\frac{\partial A}{\partial \eta}(sI-A)^{-1}B\begin{bmatrix} \bar{\tau}_r \\ \bar{\tau}_g \end{bmatrix} \tag{21}$$

It then remains to define a specification of the desired characteristics of the filtered residual through $T_{zf}(s)$. The following form was selected with the goal of arriving at a low pass causal filter. Returning to the standard form in Fig. 4, it is recognized that the presented model for the drive train contains uncertain descriptions arising from the wind turbine power/torque coefficient variations. These are included as uncertain LTI objects in the fault to residual transfer matrix $T_{yf}(s)$. After some manipulations, it is possible to extract the uncertainty and put the system in the standard linear fractional transformation (LFT) form. However, current μ-*synthesis* tools in MATLAB allow one to solve for the desired filter $F(s)$ directly from the description in Fig. 4 with the transfer functions defined in (19)-(22).

$$T_{zf}(s) = \begin{bmatrix} \dfrac{\alpha_{\omega_r}^2}{(s+\alpha_{\omega_r})^2} & 0 & \dfrac{\alpha_{\omega_{r\eta}}}{(s+\alpha_{\omega_{r\eta}})} \\ 0 & \dfrac{\alpha_{\omega_r}^2}{(s+\alpha_{\omega_r})^2} & \dfrac{\alpha_{\omega_{g\eta}}^2}{(s+\alpha_{\omega_{g\eta}})^2} \end{bmatrix} \tag{22}$$

In this work, the DK iteration method of μ-*synthesis* was used to arrive at the filter. The designed filter when applied on or together with the primary residual generators described in Section 3, achieves the fault signatures listed in the Table 2. Note that it is possible to distinguish between any pair of faults using residuals based on 2 sensor-pairs (rotor speed, generator speed). Note that the above approach addresses the sensor faults whether they are of fixed-value or are of gain type sensor faults.

Table 2. Fault signatures for the drivetrain subsystem

Faults	Residuals						
	Filtered residuals		Raw residuals		From power/torque sensors		
	$r_{\omega r1f}$	$r_{\omega r2f}$	$r_{\omega g1}$	$r_{\omega g2}$	$r_{\omega gP1}$	$r_{\omega gP2}$	$r_{\tau g}$
$\Delta\omega_{r,m1}$ (fixed)	1	0	1	0	0	0	0
$\Delta\omega_{r,m2}$ (fixed)	0	1	0	1	0	0	0
$\Delta\omega_{r,m1}$ (gain)	1	0	0	0	0	0	0
$\Delta\omega_{r,m2}$ (gain)	0	1	0	0	0	0	0
$\Delta\omega_{g,m1}$ (fixed or gain)	0	0	0	0	1	0	0
$\Delta\omega_{g,m2}$ (fixed or gain)	0	0	0	0	0	1	0
$\Delta\tau_g$(bias)	0	0	0	0	0	0	1
$\Delta\eta$	0	0	1	1	0	0	0

5. RESULTS

In this section we give some examples of results from applying the above robust fault diagnosis approach for detecting and isolating the faults for the wind turbine as defined in the Benchmark Problem (Odgaard et. al, 2009b). The reader is referred to this paper for details of the HAWT model parameters and the discussion of the fault categories.

5.1. Pitch Subsystems

The first of blade pitch subsystem faults is a fixed value of 5^o in sensor 1 of blade pitch subsystem 1 injected at T=2000s. As shown in Fig. 5, the fault causes the first residual to cross the threshold while the second residual remains within the threshold bounds. The fault detection and isolation time for this fault is ~0.07s. The effect of the fault on the second residual is not completely decoupled. Therefore, there is a value of the fault (about 12^o) above which both residuals will cross the thresholds and the fault will not be isolated.

Figure 5 also shows the first residual for blade pitch subsystem 2 where an abrupt system or parametric fault is injected at T=2900s. The fault is unobservable until the reference input β_r deviates from zero at T=2950.32s. The fault is then detected and isolated at T_D=2952.20s. Further tuning of this diagnosis is possible via the specification of $T_{zf}(s)$ as given in equation (18).

In the low right corner of Fig. 5, the first residual for the third pitch subsystem is shown. Two faults are injected here, the first at T=2600s is a fixed value sensor fault of 10°, while the second is a slow parametric fault starting at T=3400s. The diagnostic scheme is able to detect and isolate the faults in 0.03s and 14.53s, respectively.

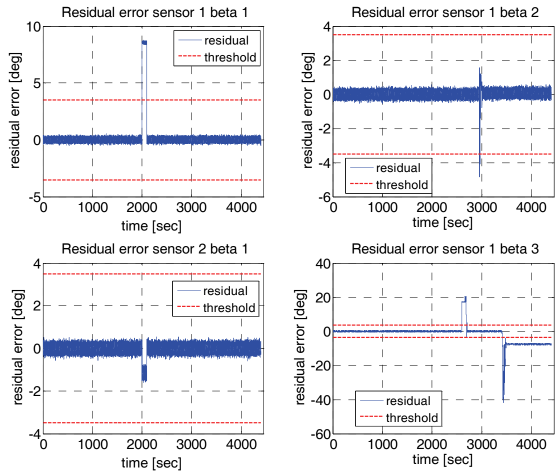


Fig. 5. Residual for sensors r_{β_1} and r_{β_2} of pitch subsystem 1 and sensor 1 (r_{β_1}) of pitch subsystems 2 and 3.

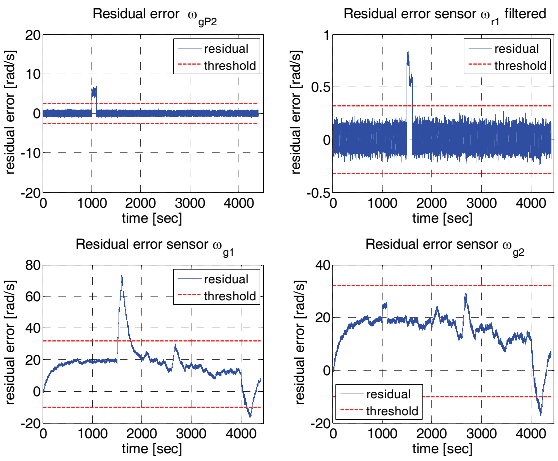


Fig. 6. Output residual $r_{\omega_g P2}$, filtered residual output $r_{\omega_{r1f}}$, unfiltered residual output $r_{\omega g1}$ and $r_{\omega g2}$.

5.2. Drivetrain Subsystem

The first fault considered in the drivetrain subsystem is a gain fault in the second generator speed sensor at T=1000s (Fig. 8). The detection and isolation of the fault takes 0.01s. The second fault in the drivetrain system is a rotor speed sensor fault corresponding to a fixed value of 1.4 rad/s injected at T=1500s. The fault is detected in 0.05s as shown in Fig. 6 by the residual $r_{\omega_{r1f}}$ crossing the threshold. Isolation is achieved in 16.5s when the residual $r_{\omega_{g1}}$ crosses the threshold. The last fault considered is a system/parametric fault at T=4000s. The fault causes both residual $r_{\omega g1}$ and $r_{\omega g2}$ to react. Detection and isolation is achieved in ~116s. Notice that the effect of this fault is suppressed in $r_{\omega_{r1f}}$ by the robust µ-synthesis filter.

6. CONCLUSIONS

The paper detailed the use of H_∞ and µ-synthesis robust control theory tools for the detection and isolation of sensor, actuator and system/parametric faults in a horizontal axis wind turbine. The proposed diagnostic scheme comprises of two parts: a primary residual generation with the parity equation approach followed by secondary residual generation/filtering based on an H_∞ optimization framework.

The diagnostic scheme described herein allows for successful detection and identification all nine faults defined in the Wind Turbine FDI Benchmark Problem (Ostergaard, 2009b). The proposed approach also gives the user a means to further tune the performance of the diagnostic schemes (e.g. for detection times or decoupling) by taking advantage of the optimization framework and the filtering specifications in the fault to (desired) residual transfer functions.

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