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Robust fault detection for wind turbines using reference model-based approach

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Abstract This paper presents a reference model-based approach for detection of different faults in a wind turbine. Stochastic uncertainty has been considered in the model of wind turbine. The fault detection scheme is so designed that the generated residual is robust against the uncertainty. For residual evaluation purpose, generalized likelihood ratio (GLR) test has been performed. Threshold is computed using the table of chi-square distribution with one degree of freedom. Occurrence of a fault is concluded whenever evaluated residual crosses the threshold. Using this approach an actuator and a sensor fault in the pitch system and a sensor fault in the drive train system are successfully detected. Results are compared with Combined Observer and Kalman Filter (COK) approach (Chen et al. 2011) used for wind turbine fault detection with this approach requiring less detection time thus providing a more useful solution to the wind industry.

1. Introduction

Wind turbines are used to convert wind energy into electrical energy. Wind energy is clean and renewable. It contributes a lot in the overall world's energy demands. Now a days, wind turbines in megawatt sizes are in operation throughout the world. As sizes of wind turbines increase, reliability becomes an important issue. A lot of work is being done to ensure service reliability and performance (Parsa and Parand, 2012). Reliability can be ensured using efficient fault detection methods. Wind turbine may work well even in the presence of mild faults but severe faults should be detected as quickly as possible so as to prevent the wind turbine from any severe damage.

A three-blade horizontal-axis wind turbine is considered in this paper. Blades of the turbine are facing the wind direction. These blades are connected to the rotor. As wind turns the blades, they cause the rotor shaft or the low-speed shaft to rotate. A gear box is used to upscale the speed to a level at which generator can generate electricity. There are two regions of operation; partial load region and full load region. Power production in partial load region is controlled by converter reference torque control, where as in the full load region, the objective is achieved with the help of pitching the blades of the wind turbine. Feedback mechanism (Elnaggar and Khalil, 2014) that is highly developed is employed for the purpose.

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The last three decades witnessed tremendous efforts in the area of fault detection and isolation both in academia and application. For a good insight, the interested reader is referred to Gertler et al. (1998), Blanke (2003), Ding (2008), Isermann (2011), Khan (2011) and Chen and Patton (1999). In the recent past, fault detection and tolerance of the wind turbine has been the focus of attention of researcher community. To this end, several techniques have been proposed. An unknown input observer based design for diagnosing faults in the wind turbine converter has been reported in Odgaard and Stoustrup (2009). A set-membership approach has been proposed in Tabatabaeipour et al. (2012). An observer based scheme for estimating pitch sensor faults is described in Wei et al. (2008) and for gearbox in Sheldon et al. (2014). A scheme based on parity equations for fault detection of wind turbines is presented in Dobrila and Stefansen (2007). A technique using up–down counters for detection of various faults has been presented in Ozdemir et al. (2011). A fault detection system using data-driven technique is designed in Yin et al. (2014). In Svärd et al. (2011), an automated design method of fault detection and isolation of wind turbines is proposed. A data-based approach has been presented in Laouti et al. (2011) in which process knowledge is not required like the other model based approaches.

In this paper, reference model-based approach (Ding, 2008) is exploited for fault detection in wind turbine. Standardized wind turbine model (Odgaard et al., 2009), that is being used by the researchers throughout the world, is used for the analysis. As a result, improvements presented in this research are likely to be adopted by the wind turbine industry. Two subsystems; that is; drive train system and pitch system are considered. Stochastic uncertainty is considered in the parameters of these systems. There are various causes of such model uncertainities including manufacturing tolerances, aging, insect and dirt contamination. Manufacturing tolerances mean that there is always a difference between mathematical model and actual process even when no fault is there. If the model uncertainities are not countered false alarms or missing alarms may occur that will seriously hinder the smooth operation of the wind turbine. The proposed FD scheme is robust against model uncertainty because of the reference model strategy. An optimal reference residual model for wind turbine subsystems is developed and a fault detection filter is then designed with its gain found using a series of LMI's. LMI solution provides efficient and reliable desirable RFDF filter. It is also interesting that there is impulsive change in the residual against some faults in the system. This, in practice, possesses difficulty in detecting such fault. In order to enhance the detectability of these faults, a post filter is proposed. Intuitively, the residual signal should be zero for fault-free case and deviate from zero otherwise. It is interesting to note that, in practice, the generated residual is non-zero even in the absence of fault in the system. Further processing of the residual is, therefore, needed. This stage includes residual evaluation and threshold setting. A systematic design of threshold for FD purpose has also been addressed in the literature, see for instance, Ding (2008), Khan and Ding (2011) and Abid et al. (2009). In this work, GLR has been used for evaluation and threshold design purpose. Threshold is found using the table of chi-square distribution with 1 degree of freedom. Then GLR test is applied that is famous for change detection. In this test, occurrence of a fault is declared whenever evaluated residual crosses the pre-defined threshold.

The rest of the paper is organized as follows: Brief introduction to the wind turbine system and model of different subsystems is given in Section 1. Reference model-based approach has been presented in Section 2. Generalized likelihood ratio test is given in Section 3. Simulation results to show the effectiveness of the proposed approach are shown in Section 4. Finally a conclusion is drawn in Section 5.

2. Mathematical model of wind turbine

A three-blade horizontal-axis wind turbine is considered in this paper. This turbine works on the principle that wind acts on the three blades of the turbine resulting in a motion of the rotor shaft. The rotational speed is upscaled with the help of a gear box to a speed at which generator can generate electricity. Rotational speed is controlled in two ways: converter reference torque control and pitch angle control of the turbine blades. Converter reference torque control is used in the partial load region, whereas, pitch angle control is used in full load region of operation of the wind turbine. Pitch angle is changed using hydraulic actuators which turn the blades according to the requirement. Sensors are used to measure the pitch system position. For the drive train system, rotor and generator speeds are also measured using sensors. In this section models of different subsystems of the wind turbine including pitch system and drive train system have been presented. These models can be found in Odgaard et al. (2009).

2.1. Pitch system model

The pitch system controls the pitch angles of the blades of wind turbine. Sensors are used to measure the blades position. It is a hydraulic system with one hydraulic actuator for each blade. The pitch actuator is modeled with a second order system and its nominal dynamics are described as

$$\frac{\beta(s)}{\beta_{ref}(s)} = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \tag{1}$$

where $\beta(t)$ is pitch angle, $\beta_{ref}(t)$ is the reference to the pitch angle, ω_n is the natural frequency of the pitch actuator model, ζ is the damping ratio of the pitch actuator model. This transfer function is discretized for use in the fault detection approach. The discretized state space model is given as

$$x(k+1) = A_p x(k) + B_p u(k) \tag{2}$$

$$y(k) = C_p x(k) + D_p u(k) \tag{3}$$

where

$$A_p = \begin{bmatrix} 0.0247 & -5.536 \\ 0.04485 & 0.6226 \end{bmatrix}, \quad B_p = \begin{bmatrix} 0.04485 \\ 0.003058 \end{bmatrix}, \quad C_p = [0 \quad 123.4], \quad D_p = [0] \tag{4}$$

2.2. Drive train model

Wind rotates the blades of the wind turbine. Drive train system has gears in it to upscale the rotor speed to a level required by the generator for generation of electricity.

The nominal dynamics of the drive train are described by

$$\dot{x}_{dt} = A_{dt}x_{dt} + B_{dt}u_{dt} \tag{5}$$

$$y_{dt} = C_{dt}x_{dt} \tag{6}$$

where the state vector $x_{dt} = [\omega_r \quad \omega_g \quad \theta_\triangle]$ includes the rotor speed, the generator speed, and the torsion angle of the drive train. The input vector $u_{dt} = [\tau_r \quad \tau_g]$ includes the aerodynamic rotor torque and the generator torque. The output represents measured speeds of the generator and the rotor.

The Drive train system has unknown aerodynamic rotor torque as one of its input. It is difficult to estimate it because it involves wind speed which has a very high noise in it. This issue has been resolved by using an approach presented in Zhang et al. (2011). We note that in drive train model, the matrices B_{dt} and C_{dt} are of the following forms.

$$B_{dt} = \begin{bmatrix} \frac{1}{J_r} & 0 \\ 0 & -\frac{1}{J_g} \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} \frac{1}{55e6} & 0 \\ 0 & -\frac{1}{390} \\ 0 & 0 \end{bmatrix} \tag{7}$$

$$C_{dt} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \tag{8}$$

We observe that the aerodynamic torque only directly affects the first state variable; that is; rotor speed, which is measured. Therefore after partitioning the matrix A_{dt} into

$$A_{dt} = \begin{bmatrix} A_{dt1} & A_{dt2} \\ A_{dt3} & A_{dt4} \end{bmatrix} \tag{9}$$

where, $A_{dt4} \in \Re^{2*2}$and $A_{dt3} \in \Re^{2*1}$, give

$$\begin{bmatrix} \dot{\omega}_g \\ \dot{\theta}_\triangle \end{bmatrix} = A_{dt4} \begin{bmatrix} \omega_g \\ \theta_\triangle \end{bmatrix} + B_1\tau_g + B_2\omega_r \tag{10}$$

with $B_1 = \begin{bmatrix} -\frac{1}{J_g} & 0 \end{bmatrix}$ and $B_2 = A_{dt3}$. By defining the state vector $z_{dt} = [\omega_g \quad \theta_\triangle]$ and taking into account the measurable generator speed, we have

$$\dot{z}_{dt} = A_{dt4}z_{dt} + B_1\tau_g + B_2\omega_r \tag{11}$$

$$\omega_g = \overline{C}_{dt}z_{dt} \tag{12}$$

where $\overline{C}_{dt} = [1 \quad 0]$. Now the inputs are generator torque and the rotor speed. We have converted the system into a form in which aerodynamic rotor torque is not present.

The continuous time state space model of drive train system is discretized with the state space model given as

$$x(k+1) = A_{DT}x(k) + B_{DT}u(k) \tag{13}$$
$$y(k) = C_{DT}x(k) \tag{14}$$

where

$$A_{DT} = \begin{bmatrix} -0.9111 & 1036 \\ -0.0001543 & -0.9094 \end{bmatrix}, \quad B_{DT} = \begin{bmatrix} -3.758e-005 & 181.4 \\ 6.926e-008 & 0.01495 \end{bmatrix}, \quad C_{DT} = [1 \quad 0] \tag{15}$$

2.3. Faults considered

Two type of faults have been considered; sensor and actuator faults. Motivation for the considered faults is largely proprietary.

2.3.1. Sensor faults

Sensor fault changes the output of the system. It might become more severe, when the sensor information are feedback to controller. Sensors are used at different points in a wind turbine, for instance, for the pitch angle measurement and rotor speed measurement. Sensor faults may either be electrical like an offset in the measurement, gain factor on the measurement or they may be mechanical like a sensor break. Mathematically, the fault is represented as

$$\text{sensor fault} = \text{sensor offset} + \text{scaling} \times \text{measurement from sensor}$$

Two sensor faults (fault 1 and fault 2) are considered. Fault 1 is related to the sensor of pitch system. This fault can result in unbalanced rotation of rotor. The fault should be detected before a large error in the pitch angle measurement in order to avoid permanent damage to the wind turbine. Fault 2 is related to the sensor measuring the rotor speed. The fault detection system is required to detect this fault before this measurement error reaches some alarming value. Table 1 shows the type of sensor that may go faulty in each case.

2.3.2. Actuator faults

As the name indicates that an actuator fault occurs in the actuator of the system. Wind turbine has three pitch actuators which may all fail at once or anyone of them may fail. There failure may be a result of oil leakage from the hydraulic system resulting in low oil pressure. This is an incipient fault and once introduced can not be reversed without the system repair. Consequences of this fault may be a slower actuator response, improper rotation of the blades or even a break in severe cases. So this fault should be detected before the pressure drops to a very low value. This fault is modeled by a change in system parameters. One actuator fault (fault 3) is considered. Table 2 indicates the type of actuator that may go faulty in case of considered fault.

The faults are listed below:

Fault 1: Gain factor sensor fault of magnitude 1.2 in pitch position sensor in the time period 2300–2400 s.

Fault 2: Gain factor sensor fault of magnitude 1.4 in rotor speed sensor in the time period 1500–1600 s.

Fault 3: Actuator fault in pitch actuator caused by low oil pressure due to hydraulic leakage in the time period 3500–3600 s.

Table 3 shows how the parameters are effected when a fault occurs.

3. Problem formulation

In this section, we use reference model-based approach (Ding, 2008) to design a fault detection scheme for pitch and drive train system. In what follows, we present briefly the reference model approach. The interested reader is referred to Ding (2008) for detailed study.

Consider a discrete time uncertain system having both disturbance and fault in it.

$$\begin{aligned} x(k+1) &= \overline{A}x(k) + \overline{B}u(k) + \bar{E}_d d(k) + E_f f(k) \\ y(k) &= \overline{C}x(k) + \overline{D}u(k) + \bar{F}_d d(k) + F_f f(k) \end{aligned} \tag{16}$$

Table 1 Fault with associated sensor.

Fault No.	Sensor type
Fault 1	Encoder
Fault 2	Speed encoder

Table 2 Fault with associated actuator.

Fault No.	Actuator type
Fault 3	Hydraulic actuator

Table 3 Variation in system parameters due to the occurrence of a fault.

Fault No.	Without fault	With fault
Fault 1	β	1.2β
Fault 2	ω_r	$1.4\omega_r$
Fault 3	$\omega_n = 11.11,\ \zeta = 0.6$	$\omega_n = 3.42,\ \zeta = 0.9$

where

$$\overline{A} = A + \triangle A, \quad \overline{B} = B + \triangle B, \quad \overline{C} = C + \triangle C \tag{17}$$

$$\overline{D} = D + \triangle D, \quad \bar{E}_d = E_d + \triangle E, \quad \bar{F}_d = F_d + \triangle F \tag{18}$$

where $\triangle A, \triangle B, \triangle C, \triangle D, \triangle E_d, \triangle F_d$ represent model uncertainties that satisfy the relationship.

$$\begin{bmatrix} \triangle A & \triangle B & \triangle E \\ \triangle C & \triangle D & \triangle F \end{bmatrix} = \sum_{i=1}^{l} \left(\begin{bmatrix} A_i & B_i & E_i \\ C_i & D_i & F_i \end{bmatrix} p_i(k) \right) \tag{19}$$

where $p_i(k)$ represent model uncertainties and is expressed as a stochastic process with mean = 0 and variance = $diag\{\sigma_1, \sigma_2, \ldots\ldots \sigma_i\}$. The matrices $A_i, B_i, C_i, D_i, E_i, F_i$ are known. The fault detection filter is given by

$$\begin{aligned} \hat{x}(k+1) &= Ax(k) + Bu(k) + L(y(k) - \hat{y}(k)) \\ \hat{y}(k) &= C\hat{x}(k) + Du(k), \quad r(k) = V(y(k) - \hat{y}(k)) \end{aligned} \tag{20}$$

where L and V represent gain of filter and post filter respectively. $r(k)$ is the residual signal. Let

$$e(k) = x(k) - \hat{x}(k) \tag{21}$$

The residual generator for (16) is given as:

$$\begin{aligned} e(k+1) &= (\overline{A} - L\overline{C})e(k) + (E_f - LF_f)f(k) - L\bar{F}_d d(k) \\ r(k) &= V(\overline{C}e(k) + F_f f(k) + \bar{F}_d d(k)) \end{aligned} \tag{22}$$

Our objective is to minimize the performance index.

$$J = E[(r(k) - r_{ref}(k))^T (r(k) - r_{ref}(k))] \tag{23}$$

This minimization is performed with a proper selection of L and V. In the above equation r_{ref} stands for the reference model given by

$$x_{ref}(k+1) = A_{ref} x_r ef(k) + E_{f,ref}(k) + E_{d,ref} d(k) \tag{24}$$

$$r_{ref}(k) = C_{ref} x_r ef(k) + F_{f,ref}(k) + F_{d,ref} d(k) \tag{25}$$

where $A_{ref} = A - L_{opt}C, E_{f,ref} = E_f - L_{opt}F_f, E_{d,ref} = E_d - L_{opt}F_d, C_r ef = V_{opt}C, F_{f,ref} = V_{opt}F_f, F_{d,ref} = V_{opt}F_d$. The filter parameters V_{opt} and L_{opt} are known as reference parameters and by solving the following coupled Ricatti equation for X_d and L_d.

$$\begin{bmatrix} AX_dA^T - X_d + E_dE_d^T & AX_dC^T + E_dF_d^T \\ CX_dA^T + F_dE_d^T & CX_dC^T + F_dF_d^T \end{bmatrix} \begin{bmatrix} I \\ L_d \end{bmatrix} = 0 \tag{26}$$

and then we find a matrix H by solving $HH^T = CX_dC^T + F_dF_d^T$. Once H is found, W_d is computed by taking the left inverse of the H matrix. Finally L_{opt} and V_{opt} are found as $L_{opt} = -L_d^T, V_{opt} = W_d$. This reference model has the ability that it provides disturbance attenuation and fault sensitivity over the whole frequency ranges. It means that the filter thus designed provides maximum robustness against disturbances and enhances sensitivity to faults.

3.1. Residual generation

As discussed above, we are interested to design a residual generator by keeping in view the reference model so that the following performance index is minimized

$$J = E[(r(k) - r_{ref}(k))^T (r(k) - r_{ref}(k))] \tag{27}$$

To this end, the results of the following theorem (Ding, 2008) are important.

Theorem 3.1. *Consider the uncertain system (16), the residual generator (22), and the reference model (24). The minimization problem (27) is solvable if there exist matrices* $V, Y, P_1 = P_1^T > 0, P_2 = P_2^T > 0, P_3 = P_3^T > 0, \alpha_1 > 0$ *and* $\alpha_2 > 0$ *such that the following LMIs are solvable*

$$\begin{bmatrix} P_1 & 0 & \Xi_1 & 0 & \Xi_2 & \Xi_3 \\ * & P_2 & 0 & \Xi_4 & \Xi_5 & \Xi_6 \\ * & * & P_1 & 0 & 0 & 0 \\ * & * & * & P_2 & 0 & 0 \\ * & * & * & * & I & 0 \\ * & * & * & * & * & I \end{bmatrix} > 0 \tag{28}$$

$$\begin{bmatrix} P_1 & 0 & C^TV^T \\ * & P_2 & -C_{ref}^T \\ * & * & \alpha_1^2 I \end{bmatrix} \geqslant 0 \tag{29}$$

$$\begin{bmatrix} I & 0 & F_d^TV^T - F_{d,ref}^T \\ * & I & F_f^TV^T - F_{f,ref}^T \\ * & * & \alpha_2^2 I \end{bmatrix} \geqslant 0 \tag{30}$$

$$\begin{bmatrix} -\widehat{P} & N_0^T\overline{P} & N_1^T\overline{P} \\ * & -\overline{P} & 0 \\ * & * & -\sigma_1^{-2}\overline{P} \end{bmatrix} < 0 \tag{31}$$

$$\begin{bmatrix} -\gamma_1^2\overline{P} & C_{r,0}^T & C_{r,1}^T \\ * & -I & 0 \\ * & * & -\sigma_1^{-2} I \end{bmatrix} \leqslant 0 \tag{32}$$

$$\begin{bmatrix} -\gamma_2^2 I & T_{r,1}^T \\ * & -\sigma_1^{-2} I \end{bmatrix} \leqslant 0 \tag{33}$$

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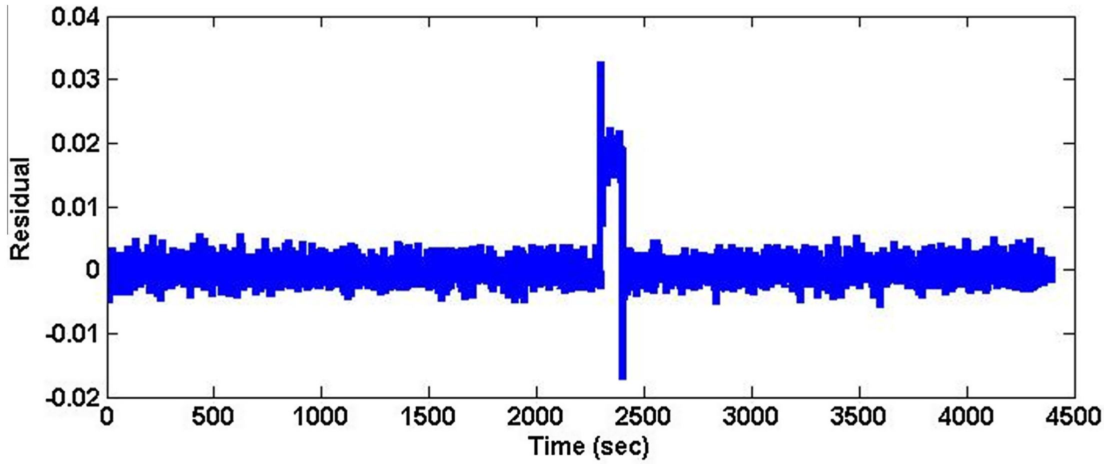

Fig. 1 Residual for gain factor sensor fault in pitch system.

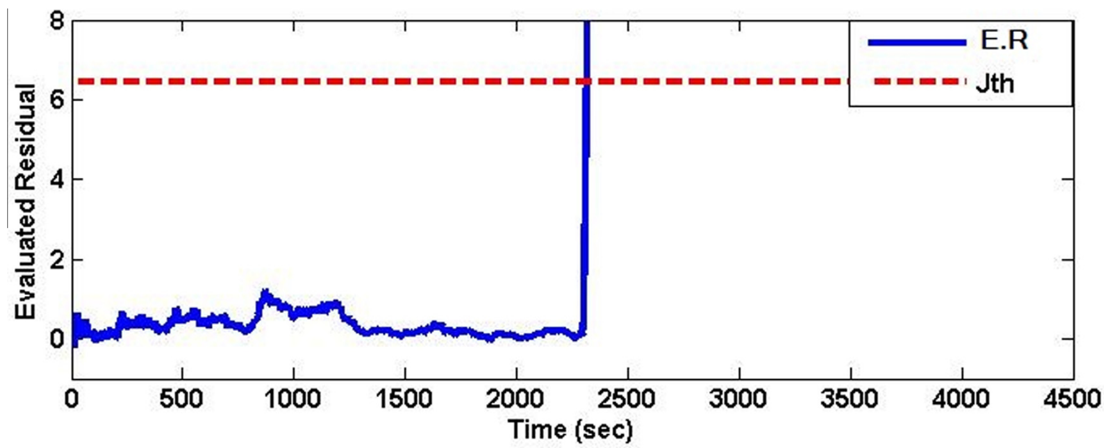

Fig. 2 GLR test result (E.R = evaluated residual) for gain factor sensor fault in pitch system with false alarm rate of .0003 ensured.

where

$$\Xi_1 = P_1A - YC, \quad \Xi_2 = P_1E_d - YF_d, \quad \Xi_3 = P_1E_f - YF_f,$$

$$\Xi_4 = P_2A_{ref}, \quad \Xi_5 = P_2E_{d,ref}, \quad \Xi_6 = P_2E_{f,ref}$$

$$\overline{P} = \begin{bmatrix} P_3 & 0 \\ 0 & P_1 \end{bmatrix} > 0$$

$$\widehat{P} = \begin{bmatrix} \overline{P} & 0 & 0 & 0 \\ 0 & I & 0 & 0 \\ 0 & 0 & I & 0 \\ 0 & 0 & 0 & I \end{bmatrix}$$

$$N_0 = \begin{bmatrix} A & 0 & B & E_d & E_f \\ 0 & A - LC & 0 & E_d - LF_d & E_f - LF_f \end{bmatrix}$$

$$N_i = \begin{bmatrix} A_i & 0 & B_i & E_i & 0 \\ 0 & A_i - LC_i & B_i - LD_i & E_i - LF_i & 0 \end{bmatrix}$$

$$C_{r,0} = [0 \quad V \quad C].$$

Once the LMIs are solved, the filter gain is set $L = P_1^{-1}Y$.

After applying this technique, residual for an actuator and a sensor fault in the pitch system and a sensor fault in the drive train system of the wind turbine has been obtained. In the next subsection residual evaluation is explained along with threshold setting that are helpful in on-line fault detection.

3.2. Residual evaluation and threshold setting

This stage is very important in an FD process. It is worth noticing that due to uncertainty and unknown disturbances, the generated residual is non-zero even in fault-free case. In order to infer the presence of fault, residual evaluation is performed. An appropriate threshold is computed and then the evaluated residual is compared with the threshold. Fault alarm is raised in case the evaluated residual exceeds the threshold value. The problem residual evaluation and threshold setting has been extensively studies in Ding (2008) for linear system and Khan and Ding (2011) and Abid et al. (2009) for nonlinear systems. For our purpose, motivated from Ding (2008), GLR test is utilized in the following way in order to compute the evaluated residual.

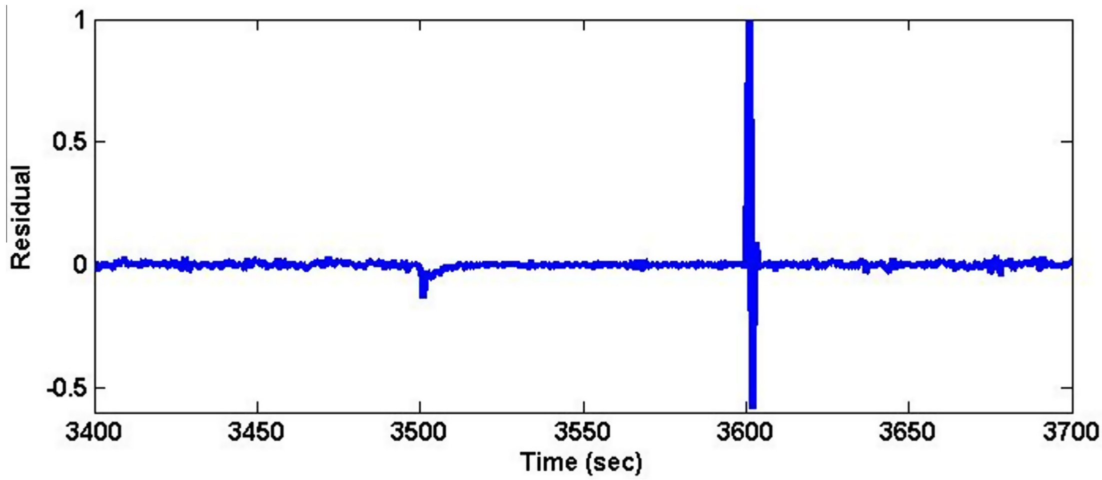

Fig. 3 Residual for actuator fault in pitch system.

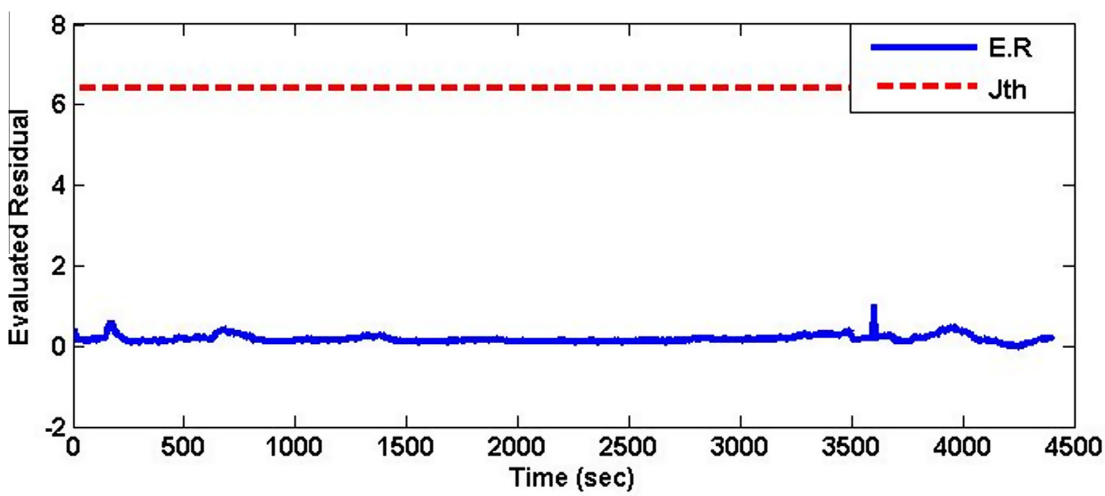

Fig. 4 GLR test result (E.R = evaluated residual) for actuator fault in pitch system with false alarm rate of .0003 ensured.

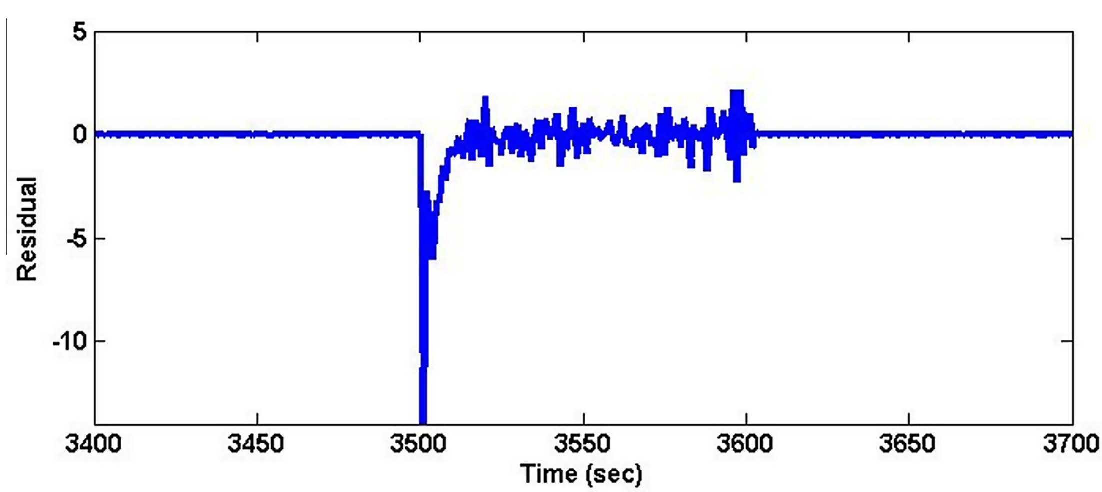

Fig. 5 Residual for actuator fault in pitch system after the use of proposed filter.

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$$S^{k+1} = \alpha S^k + (1-\alpha)\left(\gamma_{y,k+1} - \frac{1}{2}y_{k+1}\right)^T \gamma^{-1} y_{k+1} \quad (34)$$

Here S^{k+1} represents $(k+1)$th sample of evaluated residual. y_{k+1} represents $(k+1)$th sample of residual obtained from robust observer.

$\alpha = \frac{k}{k+1}$; $\gamma_{y,k+1} = \gamma_{y,k} + y_{k+1}$

where

$$\gamma_{y,k} = \left(\sum_{i=1}^{k} y_i\right), \quad k = 1, \ldots\ldots. \quad (35)$$

Using this recursive algorithm, evaluated residual S^{k+1} is computed and compared with a threshold. An important step in finding the threshold is to find a tolerant limit for disturbances and model uncertainties under fault free operation. Threshold is found using the table of chi-square distribution with one degree of freedom. At the instant we get evaluated residual greater then the threshold, it is declared that a fault has occurred and an alarm is generated.

4. Simulation results

In this section simulation results are shown. The simulation run time is 4400 s.

4.1. Results for pitch system

Fig. 1 shows the residual plot for the case of a gain factor sensor fault of magnitude 1.2 inserted in the pitch system measurement at the time interval of 2300–2400 [s]. From the plot of residual it can be easily seen that the residual remains around zero before and after the occurrence of fault but during the fault interval the residual rises significantly. Also from Fig. 2, it is observed that evaluated residual crosses the threshold after the occurrence of fault. This fault is detected at the time instant 2316 s, i.e 16 s after the occurrence of fault.

Fig. 3 shows the residual for the case of an actuator fault in pitch actuator caused by low oil pressure in the time period 3500–3600 [s]. From the plot of residual, it can be seen that as the fault occurs, the residual rises in the form of a very thin impulse. Fault detection devices require that the width of that impulse should be enough so that they can easily detect that rise. Also from Fig. 4, we can see that this fault is not detected successfully as the threshold is not being crossed at the fault instant. What we require is to increase the width of that impulse, so that detection becomes possible. For this purpose we propose a filter given as

$$Gz = \frac{T_d s}{1 + \gamma T_d s} \quad (36)$$

After the use of that filter with proper tuning, we get the residual as shown in Fig. 5. Now we see that the width of the residual at the fault instant has increased and now the fault is easily detected. This is also shown by the GLR test result in Fig. 6. This fault is detected 27 s after the occurrence of fault with an ensured false alarm rate less then .0003. L_{opt} and V_{opt} for the considered faults in pitch system are enlisted in Table 4 and the values of threshold are listed in Table 5.

Table 4 L_{opt} and V_{opt} values for pitch system faults.

Fault No.	L_{opt}	V_{opt}
Fault 1	$\begin{bmatrix} -0.0448 \\ 0.0054 \end{bmatrix}$	0.1653
Fault 3	$\begin{bmatrix} -0.0448 \\ 0.0054 \end{bmatrix}$	0.1653

4.2. Results for drive train system

A gain factor rotor sensor fault of magnitude 1.4 is inserted in rotor speed measurement in the time interval 1500–1600 s. The plot of residual is shown in Fig. 7 clearly indicating that it remains nearly zero before the occurrence of fault. As the fault occurs residual rises and reaches a significant height. After the fault interval residual again drops to a very low value indicating no fault. Fig. 8 is the GLR test result plot indicating evaluated residual around zero before the fault. As the fault is

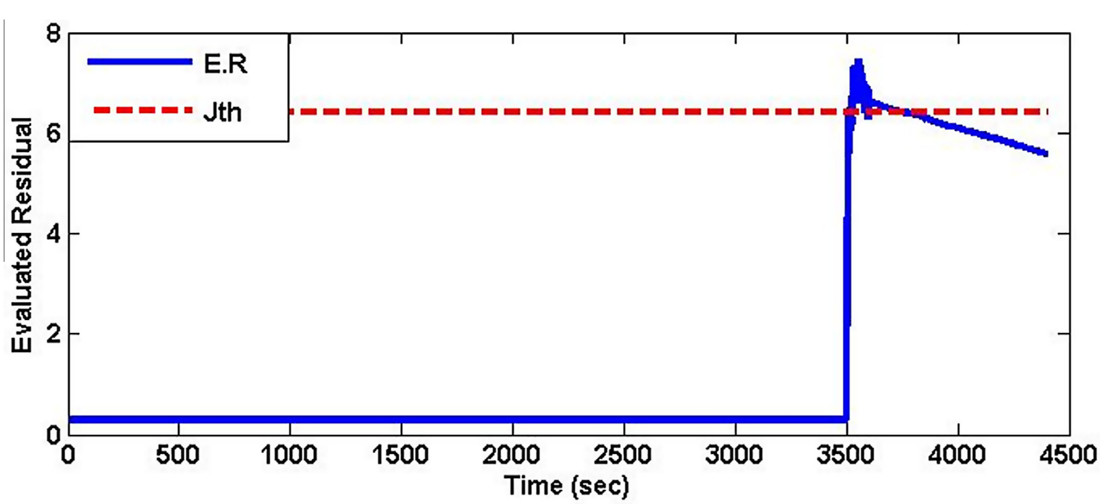

Fig. 6 GLR test result (E.R = evaluated residual) for actuator fault in pitch system after the use of proposed filter with false alarm rate of .0003 ensured.

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Table 5 Threshold (J_{th}) values for pitch system faults.

Fault No.	J_{th}
Fault 1	6.425
Fault 3	6.425

introduced in the subsystem, it rises and crosses the threshold. This fault is detected at the time instant 1511 s, i.e 11 s after the occurrence of fault.

Table 6 enlists the value of V_{opt} and L_{opt} for this fault. Threshold computed for the considered fault in drive train system is given in Table 7.

The results generated by applying reference model-based (RMB) fault detection algorithm on the wind turbine benchmark have been compared with Combined Observer and Kalman Filter (COK) approach (Chen et al., 2011). Fault detection times (in s) of both of these works are listed in Table 8. From the table, it can be seen that we got improved results for Fault 2 (Gain factor sensor fault of magnitude 1.2 in pitch 2 position sensor), Fault 4 (Gain factor sensor fault

Table 6 L_{opt} and V_{opt} values for drive train system faults.

Fault No.	L_{opt}	V_{opt}
Fault 2	$\begin{bmatrix} -0.8076 \\ -0.0002 \end{bmatrix}$	0.0189

Table 7 Threshold (J_{th}) value for drive train fault.

Fault No.	J_{th}
Fault 2	3.9395

Table 8 Results of COK and RMB in terms of detection time (s).

Approach	COK (s)	RMB (s)
Fault 1	19.24	16
Fault 2	17.67	11
Fault 3	34	27

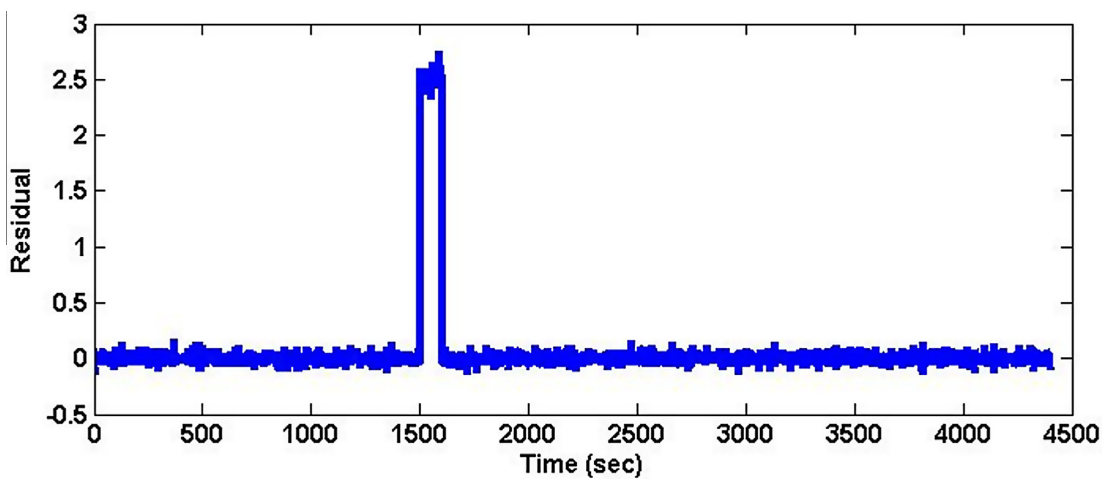

Fig. 7 Residual for gain factor sensor fault in drive train system.

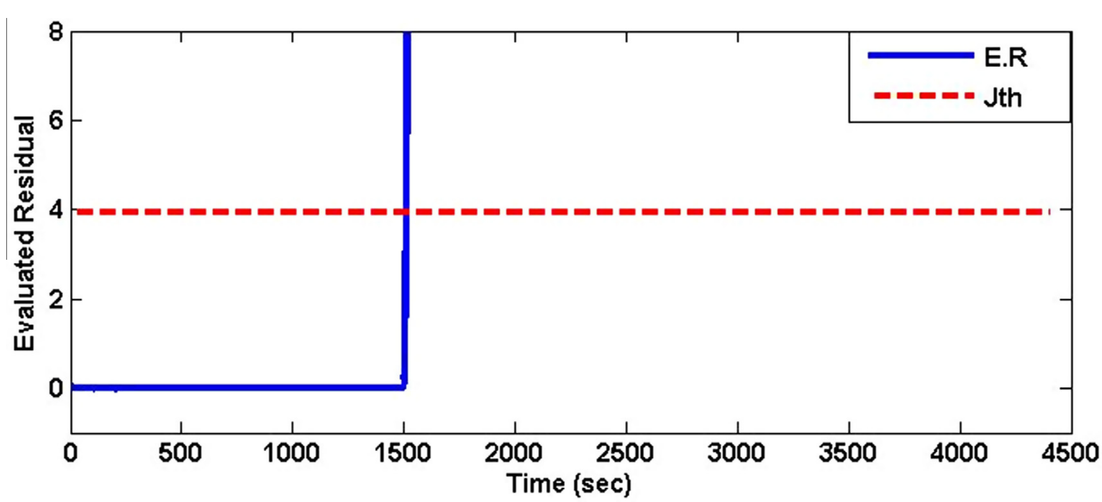

Fig. 8 GLR test result (E.R = evaluated residual) for gain factor sensor fault in drive train system with false alarm rate of .005 ensured.

of magnitude 1.4 in rotor speed sensor) and Fault 7 (Actuator fault in pitch actuator 3 caused by low oil pressure). The comparison shows that reference model-based approach is quite efficient in detecting these faults.

5. Conclusion

In this paper, reference model-based approach is utilized to address robust fault detection problem in a wind turbine. Stochastic uncertainty is considered in the model of wind turbine subsystems. The proposed FD scheme is robust against disturbances and model uncertainties and sensitive against faults. After residual generation, GLR is used for residual evaluation purpose. An actuator and a sensor fault in the pitch system and a sensor fault in the drive train system are successfully detected. Results are compared with Combined Observer and Kalman Filter (COK) approach for wind turbine fault detection. Results show that the detection time of the aforementioned faults has been improved with reference model-based approach. The proposed post filter enhanced the fault detection capability.

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