Fault Detection and Isolation of a Benchmark Wind Turbine using the Likelihood Ratio Test

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Abstract: In this paper the generalized likelihood ratio (GLR) test and the associated statistical fault detection tools are used to detect and isolate faults in the wind turbine benchmark problem. The most challenging task in the wind turbine problem is accurate detection and isolation of the fault within the stringent time constraints which are set for each of the faults. On the other hand due to the practical implementation issues, the computational effort should be as low as possible. Inaccurate measurement of wind speed, high nonlinearities in the drive train model and correlated process and measurement noises are other critical issues which are dealt with in the current work.

Keywords: Generalized likelihood ratio (GLR), Kalman filter, fault detection and isolation.

1. INTRODUCTION

Wind turbines are a new sources of generating green energy and like any other novel technology they also present many challenges. Recently, the dependence on electricity generated by the wind energy has significantly increased and as a result the maintenance and optimal operation of the wind turbines have become critical issues. The wind turbine problem can be approached from two different aspects; the optimal control and fault detection and isolation. The main focus of the optimal control strategy is to produce the maximum power with respect to the constraints of the machinery, while the goal of the fault detection and isolation system is to detect and diagnose any type of fault which may occur. The fault detection and isolation system can detect any type of malfunction in the system and meanwhile can provide the operator with enough information about the location and the magnitude of the fault. The proposed optimal control and fault detection systems can be combined to form a fault tolerant control scheme which automatically compensates for the faults. Consequently, not only electricity generation and durability of machinery could be maximized but also the maintenance cost would be reduced. The models proposed by Odgaard et al. (2009), provide the necessary means for a model based approach towards fault tolerant control of the wind turbines and based on these models the current study aims to propose a supervisory fault detection and isolation scheme. Most of the model based methods rely on statistical tests such as fault detection and confirmation tests (FDT and FCT) for detecting the fault occurrence sample (Narasimhan and Mah (1988) and Prakash et al. (2002)). The variation of generalized likelihood ratio (GLR) test proposed by Narasimhan and Mah (1988) and inherited in studies by Prakash et. al (2002,2005), has been widely used for the purpose of isolation of the fault as well as estimating its magnitude. One of the main limitations of this methodology, is that the fault signature matrices are not applicable to nonlinear plants, unless such systems can be represented as multiple locally linear systems. However, this restriction can be overcome by means of the fault mode Kalman filters which were introduced by Deshpande et al. (2009). It is worth mentioning that, the fault mode Kalman filters will significantly increase the computational load in comparison with the simple pre-computed signature matrices. Nevertheless, the use of fault mode observers seems to be inevitable in the face of nonlinear systems or linear ones which are subject to non-additive faults.

In the current study, the GLR test along with the statistical FDT and FCT tests are used in order to detect and isolate the faults. In order to achieve high reliability in the fault detection and isolation (FDI) system, a distributed scheme has been proposed. In other words, a separate and dedicated supervisory module has been designed for each of the wind turbine components. This distributed scheme will not only improve the availability of the FDI system, but can also reduce the complexity of a centralized fault detection system. This paper is organized as follows; in the third section, the design of FDI system for each of the wind turbine components as well as their relevant fault mode observers are discussed. Section 4 provides a brief review of the generalized likelihood ratio while section 5 is dedicated to results and practical issues followed by the discussion and concluding remarks in section 6.

2. DEFINITION OF THE PROBLEM

Details of the wind turbine benchmark problem can be found in Odgaard et al. (2009) and the details of the problem are not included here for the sake of brevity. Furthermore, all the models used in this study are reported in Odgaard et al. (2009).
3. DISTRIBUTED FDI SYSTEM

For the sake of brevity, the basics of the Kalman filter based fault detection and diagnosis are omitted here and the interested reader is referred to Narasimhan and Mah (1988), Prakash et al. (2002) and Deshpande et al. (2009). In this study 5 separate FDI modules have been designed for faults related to the variables $\beta_1$, $\beta_2$, $\beta_3$, $\tau_3$ and the drive train. The most crucial challenge in designing the FDI module for the pitch system is the fact that the process and measurement noise are correlated due to the existence of the feedback signal which will be discussed in detail in the next section. On the other hand, although the drive train model seems to be a linear one, the nonlinearities associated with computation of input $\tau_3$ renders it as a nonlinear system. Moreover, the noisy measurements of the wind speed will add to the uncertainties of the drive train model.

3.1 State Estimation of the Pitch System

The model provided by Odgaard et al. (2009) includes a feedback system which is defined as follows:

$$b_i(k) = \beta_i(k) - \frac{1}{2}(\beta_i(k) + e_1(k) + \beta_i(k) + e_2(k))$$

(1)

where, $e_1(k)$ and $e_2(k)$ represent the first and second measurement noise sequences, respectively. This feedback signal is used to reduce the error between the setpoint of the pitch system and the measured pitch angle. However, including this feedback signal will result in subtracting an average of the measurement noise terms -at each time instant- from the input of the model in the normal operating condition and consequently, this process noise should be taken into account in the state estimation. It should be noted that this sequence will be no longer white in the case of fault occurrence and the fault signature will propagate through this feedback signal. Consider the following model where process and measurement noise sequences are correlated:

$$x_k = F_{k-1}x_{k-1} + G_{k-1}u_{k-1} + J_{k-1}w_{k-1}$$

(2)

$$y_k = H_x x_k + v_k$$

(3)

where, $x$ and $u$ represent the true state and the input signal, respectively. The process and measurement noise sequences $w(k)$ and $v(k)$ are assumed to be white with zero mean i.e. $w_k \sim (0, Q_k)$ and $v_k \sim (0, R_k)$ where the covariance matrices $R_k$ and $Q_k$ are known. The correlation between the noise sequences can then be defined as follows:

$$E[ww^T] = Q_k \delta_{k-j}, \quad E[vv^T] = R_k \delta_{k-j}$$

(4)

$$E[ww^T] = M_k \delta_{k-j+1}$$

(5)

where $\delta$ is the Kronecker delta function. In the normal operating condition the auto-covariance and cross-covariance matrices can be found to be:

$$E[ww^T] = \frac{1}{2} \sigma_w^2 \delta_{k-j}, \quad E[vv^T] = \begin{bmatrix} \sigma_v^2 & 0 \\ 0 & \sigma_v^2 \end{bmatrix} \delta_{k-j}$$

where $\sigma_w^2$ is the variance of angle measurement noise. It is straightforward to develop the optimal Kalman filter for this model and the relevant equations can be summarized as followings (Simon (2006)):

$$\dot{x}(k-1) = F_{k-1} \dot{x}(k-1) + G_{k-1}u_{k-1}$$

(6)

$$P(k-1) = F_{k-1}P(k-1)F_{k-1}^T + J_{k-1}Q_{k-1}J_{k-1}^T$$

(7)

$$K_k = (P(k-1)H_x^T + J_k(M_k \times \begin{pmatrix} H_x \mu(k-1)H_x^T + H_{k-1}J_{k-1}M_k + \mu_{k-1}J_{k-1}^T H_{k-1}^T + R_{k} \end{pmatrix}^{-1})$$

(8)

$$P(k) = P(k) - K_k (H_x P(k-1) + \mu_{k-1} J_{k-1}^T)$$

(9)

It should be noted that in Simon (2006), the matrix $J_k$ is assumed to be unity and the proof is based on this assumption. However, in the pitch system model $J_k = G_2$. In order to avoid complexity and since the dynamics of the systems are assumed to be time-invariant during the normal operating condition, the subscript $k$ will be omitted in the rest of this work. In this work all the models related to the pitch system were discretized using the “ZOH” method with $T_s = 0.01$ seconds.

Fault Mode Observers for $\beta_1$: The $\beta_1$ FDI module should be capable of detecting failure of a sensor which is stuck at a certain value. In order to deal with this fault the measurement output equation shall be modified as follows (Deshpande et al. (2009)):

$$y_{\beta_1}(k) = H_x \tilde{x}(k) + [b_{\beta_1} - e_{\beta_1} H_x \dot{x}(k)]e_{\beta_1}(k-t)$$

(10)

where $b_{\beta_1}$ is the constant value at which the ith sensor reading is stuck and $e_{\beta_1}$ is the unitary column vector representing the location of the fault. The step function and fault occurrence sample are denoted by $\delta(k-t)$ and $t$, respectively.

Remark 1. In the models provided by Odgaard et al. (2009), the additive noise is not considered to be present in case of sensor failures. However, the noise term can be easily included in the fault mode Kalman filter.

After fault occurrence the feedback signal defined in (1) will be no longer white noise and it will contain the fault component. In case of the first sensor failure, this signal can now be represented as:

$$b_1(k) = \beta_1(k) - \frac{1}{2}(b_{\beta_1} + \beta_1(k) + e_2(k))$$

(11)

$$= \frac{1}{2}(b_{\beta_1} - \beta_1(k)) - \frac{1}{2}e_2(k)$$

(12)

Noticing the fact that $w(k) = -\frac{1}{2}(b_{\beta_1} - \beta_1(k)) - \frac{1}{2}e_2(k)$, it seems logical to split this signal into two parts. The first part $-\frac{1}{2}(b_{\beta_1} - \beta_1(k))$ can be treated as an external input to the model while the process noise can be redefined as $w(k) \equiv w(k) = -\frac{1}{2}e_2(k)$; the auto and cross-covariance matrices can then be easily found to be:

$$E[ww^T] = \frac{1}{4} \sigma_w^2 \delta_{k-j}, \quad E[vv^T] = \begin{bmatrix} 0 & 0 \\ 0 & \sigma_v^2 \end{bmatrix} \delta_{k-j}$$

(13)
Consequently, observer equations (4) and (8) can be redefined as follows:

\[
\mathbf{\dot{x}}(k|k-1) = \mathbf{F}\mathbf{x}(k-1|k-1) + \mathbf{G}\mathbf{u}_{k-1}
\]

\[
+ \mathbf{G}
\left( -\frac{1}{2}(\mathbf{b}_{1} - \beta_1(k)) \right)
\]

\[
= \mathbf{F}\mathbf{x}(k-1|k-1) + \mathbf{G}
\left( -\frac{1}{2}(\mathbf{b}_{1} - \mathbf{e}^T_{y1}\mathbf{H}\mathbf{x}(k-1|k-1)) \right)
\]

(11)

\[
\mathbf{y}_y(k) = \mathbf{h}(k) - \mathbf{H}\mathbf{x}(k|k-1)
\]

\[
+ [\mathbf{b}_{y1} - \mathbf{e}^T_{y1}\mathbf{H}\mathbf{x}(k|k-1)]\mathbf{e}_{y1}\mathbf{S}(k-t)
\]

(12)

\[
\text{Fault Mode Observers for } \beta_2: \text{ The fault mode observer for}
\]

\[
\text{pitch actuator 2 is straightforward since only the values of } \omega_0 \text{ and } \zeta \text{ will change in case of fault occurrence but the fault}
\]

\[
\text{which corresponds to the change in the gain matrix needs to be}
\]

\[
\text{formulated. In this case the output measurement equation}
\]

\[
\text{can be expressed as:}
\]

\[
\mathbf{y}_y(k) = \mathbf{h}(k) - \mathbf{H}\mathbf{x}(k)
\]

\[
+ [\mathbf{b}_{y1} - \mathbf{e}^T_{y1}\mathbf{H}\mathbf{x}(k|k-1)]\mathbf{e}_{y1}\mathbf{S}(k-t)
\]

(14)

where \( \mathbf{b}_{y1} \) is the new gain of the \( i \)-th sensor in the model. The

\[
\text{feedback signal in (1), in case of change in the gain matrix of sensor can no longer be represented as a summation of white noise}
\]

\[
\text{sequences and is transformed as follows:}
\]

\[
\beta_2(k) = \mathbf{\beta}_2 - \frac{1}{2} \left[ \begin{array}{c}
\beta_2(k) + e_1(k) + b_2(\beta_2(k) + e_2(k))
\end{array} \right]
\]

\[
= \mathbf{\beta}_2(k) - \frac{1}{2} \left[ \begin{array}{c}
\beta_2(k) + \beta_2(k)
\end{array} \right]
\]

\[
+ [\mathbf{b}_{y1} - \mathbf{e}^T_{y1}\mathbf{H}\mathbf{x}(k|k-1)]\mathbf{e}_{y1}\mathbf{S}(k-t)
\]

(13)

\[
\text{In this case it is assumed that the multiplicative change happens in the gain of sensor no.2. Similar to the procedure which was}
\]

\[
\text{used for } \beta_1, \text{ equation (15) can be split into two parts. The first part, } \frac{1}{2}(\mathbf{b}_{2} - 1)\mathbf{b}_{2}, \text{ will be considered as an extra input to the}
\]

\[
\text{pitch no.2 model while the second part, } \frac{1}{2}(e_1(k) + b_2e_2(k)), \text{ will be treated as the process measurement noise. The auto- and}
\]

\[
\text{cross-covariance matrices of noise sequences be expressed as:}
\]

\[
E[\mathbf{w}_k\mathbf{v}_{j}^T] = \begin{bmatrix}
0 & -\frac{1}{2}\sigma_\beta^2
\end{bmatrix}
\delta_{k-j}
\]

\[
E[\mathbf{v}_k\mathbf{v}_{j}^T] = \begin{bmatrix}
\sigma_\beta^2 & 0
0 & b_2^2\sigma_\beta^2
\end{bmatrix}
\delta_{k-j}
\]

(15)

\[
\text{In a similar manner to } \beta_1, \text{ observer equations (4) and (8) can be redefined as follows:}
\]

\[
\mathbf{\dot{x}}(k|k-1) = \mathbf{F}\mathbf{x}(k-1|k-1) + \mathbf{G}
\left( -\frac{1}{2}(\mathbf{b}_{2} - \beta_2) \right)
\]

\[
= \mathbf{F}\mathbf{x}(k-1|k-1) + \mathbf{G}
\left( -\frac{1}{2}(\mathbf{b}_{2} - \mathbf{e}^T_{y2}\mathbf{H}\mathbf{x}(k-1|k-1)) \right)
\]

(16)

\[
\text{The residuals in this case can be formulated as:}
\]

\[
\gamma_y(k) = \mathbf{y}(k) - \mathbf{H}\dot{\mathbf{x}}(k|k-1)
\]

\[
+ [\mathbf{b}_{y2} - \mathbf{e}^T_{y2}\mathbf{H}\mathbf{x}(k|k-1)]\mathbf{e}_{y2}\mathbf{S}(k-t)
\]

(17)

\[
\text{Fault Mode Observers for } \beta_3: \text{ The fault which corresponds}
\]

\[
to the failure of a sensor stuck at a certain value is similar to the fault in } \beta_1 \text{ and as a result, its fault mode Kalman filter is}
\]

\[
\text{the same of the one which was developed previously. However, the fault scenario explained in Odgaard et al. (2009) as slow and linear change in values of } \omega_0 \text{ and } \zeta \text{ due to problems in pitch actuator no.3, arises a need to formulate a new fault mode Kalman filter. The general structure of this fault is the same as (4)-(8) but the major difference is that the state space equations in this case are defined as follows:}
\]

\[
\mathbf{x}_k = \alpha\mathbf{F}_1\mathbf{x}_{k-1} + (1 - \alpha)\mathbf{F}_2\mathbf{x}_{k-1} + \alpha\mathbf{G}_1\mathbf{u}_{k-1}
\]

\[
+ (1 - \alpha)\mathbf{G}_2\mathbf{u}_{k-1} + \alpha\mathbf{G}_1 + (1 - \alpha)\mathbf{G}_2\mathbf{w}_{k-1}
\]

\[
= \mathbf{\alpha F}_1 + (1 - \mathbf{\alpha})\mathbf{F}_2\mathbf{x}_{k-1} + [\alpha\mathbf{G}_1 + (1 - \alpha)\mathbf{G}_2]\mathbf{w}_{k-1}
\]

\[
+ [\alpha\mathbf{G}_1 + (1 - \alpha)\mathbf{G}_2]\mathbf{u}_{k-1}
\]

(19)

\[
\text{where } 0 \leq \alpha \leq 1, \text{ and state matrices with index 1 belong to the normal operating condition while those with index 2 represent the faulty mode. In other words, the following matrices can be defined and replaced in (4)-(8) in order to obtain the fault mode observer.}
\]

\[
\mathbf{F}' = \alpha\mathbf{F}_1 + (1 - \alpha)\mathbf{F}_2, \quad \mathbf{G}' = \alpha\mathbf{G}_1 + (1 - \alpha)\mathbf{G}_2
\]

\[
\text{Remark 2. It should be noted that } \alpha \text{ changes at each time instant and therefore it is a time varying parameter. Consequently in order to achieve lower residuals and more accurate state estimates it is recommended that } \alpha(k) \text{ be computed using the following equation:}
\]

\[
\alpha(k) = \alpha(k-1) - \frac{1}{3000}
\]

(20)

\[
\text{It should be noted that, the above equation is derived for the case when } \alpha \text{ decreases from 1 to 0 and the fault is detectable before } \alpha = 0. \text{ Similarly, } \alpha(k) = \alpha(k-1) + \frac{1}{3000} \text{ on the upward}
\]
Nevertheless, since the size of FCT window would not increase beyond 36 samples in this work, this time-varying factor can be approximated considered constant for the purpose of fault isolation.

3.2 State Estimation of Generator and Converter System

The fault mode observer for the generator and converter can be derived using the Kalman filter equations for uncorrelated process and measurement noise sequences. In the model proposed by Odgaard et al. (2009), the process noise is assumed to be zero and this fact makes the state estimation problem even simpler. In this study, the converter dynamics were discretized using the “ZOH” method with $T_s = 0.01$ seconds. Regarding the distributed FDI system, it is worth mentioning that the faults related to $\tau_g$ can be independently handled without having access to the estimate of $\omega_k$ which is provided by the FDI module of the drive train. Nevertheless, for the case that faults are likely to occur in the generator component, the generator FDI module should be designed to work in series with that of the drive train.

The Kalman filter equations for $\tau_g$ are the same as those stated in Prakash et al. (2002), and for the sake brevity these equations are not included in this section. However, in order to obtain the fault mode observer, equations related to the state update and the residuals are changed as follows:

$$\begin{align*}
\hat{x}(k|k) &= \hat{x}(k|k-1) + K(k) \left( y(k) - [H\hat{x}(k|k-1) + b] \right) \quad (21) \\
\gamma_e(k) &= y(k) - [H\hat{x}(k|k-1) + b] \quad (22)
\end{align*}$$

3.3 State Estimation of the Drive Train System

At a first glance it seems that the drive train model is a linear system but the fact that $\tau_d$ is computed as follows, makes the system a nonlinear one (Odgaard et al. (2009)):

$$\tau_d(t) = \sum_{i=1}^{n} \frac{\rho \pi R^3 C_d \lambda(t) \beta_i(t)}{\omega} \nu_{ao}(t)$$

The dependency of the $\tau_d$ on the estimates of $\beta_1, \beta_2$, and $\beta_3$ make the FDI module of drive train dependent on the state estimators and FDI’s of the pitch and converter systems. Consequently, the FDI module and the state estimators of the drive train system should be working in series with those of the pitch and converter systems. On the other hand, since $\lambda(t) = \omega \frac{R}{\omega^2}$, $\tau_d$ would be a nonlinear function of variables $\omega$ - which is a state of the system- and the wind speed ($\nu_{ao}$). Furthermore, it should be noted that $C_d$ is a look-up table and this fact increases the nonlinearity and complexity of the system. Considering the aforementioned issues, it seems logical to consider the drive train system as described by the following equation:

$$\begin{align*}
x(k+1) &= A_d x(k) + B_d f(\omega, \nu_{ao}, \beta_1, \beta_2, \beta_3, \tau_d) + w(k) \\
y(k) &= x(k) + v(k)
\end{align*}$$

where $w(k)$ is an artificial process noise sequences whose variance can be used a tuning parameter which corresponds to the lumped uncertainties in the model.

Remark 3. There several sources of uncertainty associated with this nonlinear system. The wind speed is one of the major issues that degrades the quality of estimation. Since the wind speed measurement is noisy ($\nu_{meas}$) and it is the only available signal in the system, it is highly recommended that a de-noising scheme be applied to the wind measurement. For this purpose an auto-regressive (AR) model can be considered for the wind speed which can be expressed as follows:

$$\begin{align*}
v'_{\omega}(k) &= v'_{\omega}(k-1) + w_{\text{wind}}(k-1) \\
v_{\omega}(k) &= v'_{\omega}(k) + v_{\text{meas}}(k)
\end{align*}$$

where $v'(k)$ is the artificial state and $v_{\text{meas}}(k)$ is the measurement noise sequence at the hub whose variance is known. The artificial process noise $w_{\text{wind}}(k)$ is added to this model and its variance can be used as a tuning parameter for the de-noising process. In this study, the variance of this artificial signal was set equal to $10^{-3}$.

Other sources of uncertainty in the state estimator of the drive train system are the errors which are related to the state estimations of $\beta_1, \beta_2, \beta_3$ and $\tau_d$.

Fault Mode Observers for the Drive Train System: The unscented Kalman filter (UKF) is an appropriate candidate for performing the state estimation task in this system. The standard UKF formulation proposed by Wan and Merwe (2000) was used in this study and for the sake of brevity, the details are omitted here. However, since both of the fault scenarios stated in Odgaard et al. (2009) for the drive train system are related to output measurements, it would be enough to define the equations that will change in the fault mode observers. In case of change in the gain matrix, the equation which formulates the propagation of the sigma points can be expressed as:

$$Y_{i,k|k-1} = H X_{i,k|k-1} + \begin{bmatrix} (b_j - 1)e_T^j H X_{i,k|k-1} \end{bmatrix} e_T S(k-t)$$

where $X_{i,k|k-1}$ represents the $i$th sigma point which has been propagated through the dynamics of the system and $j$ and $t$ denote the location of the fault and the instant of the fault occurrence, respectively. Similarly, if two changes in gain matrices occur simultaneously, (28) can be easily extended to the following:

$$Y_{i,k|k-1} = H X_{i,k|k-1} + \begin{bmatrix} (b_j - 1)e_T^j H X_{i,k|k-1} \end{bmatrix} e_T S(k-t) + \begin{bmatrix} (b_n - 1)e_T^m H X_{i,k|k-1} \end{bmatrix} e_T S(k-t)$$

It should be noted that in the modeling of the drive train, the measurement equations are considered to be linear and therefore in equations (28-29) the change in gain is modeled as an additive term. The output estimation equation of the fault mode Kalman filter pertaining to the failure of a sensor at a certain value can be defined as:

$$Y_{i,k|k-1} = H X_{i,k|k-1} + \begin{bmatrix} (b_j - 1)e_T^j H X_{i,k|k-1} \end{bmatrix} e_T S(k-t)$$

3.4 Description of Distributed FDI system

It may be noted that the individual components of the FDI system have been discussed in detail but the main issue in a
A distributed system is how these modules are going to interact with each other. In order to design the distributed FDI system, the cause and effect relationships among the subsystems should be taken into consideration. For instance, in case of fault occurrence in pitch 1, the FDI module of the drive train should be disabled or else the fault in pitch 1 might cause deviation of drive train module from its normal operating condition and this abnormality can affect the FDI module of the drive train subsystem as well as that of pitch 1. The cause and effect matrix of the wind turbine benchmark is tabulated in Table 1 and as can be seen, the drive train estimator and FDI system are dependent on all other components in the system.

<table>
<thead>
<tr>
<th>Table 1. Cause and effect matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cause (Fault)</td>
</tr>
<tr>
<td>Drive Train</td>
</tr>
</tbody>
</table>

Based on the cause and effect matrix of the system, a distributed FDI system can be designed for the wind turbine benchmark problem. The block diagram of this system is depicted in Fig. 1 and as it can be seen, the residuals from pitch 1,2,3 can be considered:

\[
\varepsilon(k) = \gamma^T(k)V^{-1}(k)\gamma(k) \tag{31}
\]

where \( V(k) \) is the covariance matrix of the residuals. This criterion which represents the weighted residuals, follows a central \( \chi^2 \) distribution with \( n \) degrees of freedom where \( n \) is the dimension of the innovation term \( \gamma \). A certain threshold can be set for this statistic which is known as fault detection test (FDT), and in case the test exceeds the predefined threshold then it is suspected that the fault has occurred. The occurrence of a fault could be confirmed by means of another statistic which is the accumulated version of the FDT test and is known as fault confirmation test (FCT). The FCT test uses the sum of FDT test in a specified window \([t, t+N]\) and is defined as follows (Narasimhan and Mah (1988)):

\[
\varepsilon(N; t) = \sum_{k=t}^{t+N} \gamma^T(k)V^{-1}(k)\gamma(k) \tag{32}
\]

The aforementioned statistic follows a central \( \chi^2 \) distribution with \( n \times (N + 1) \) degrees of freedom. Similarly, a certain threshold can be chosen for this criterion and the fault occurrence is confirmed when this threshold is exceeded.

4. GENERALIZED LIKELIHOOD RATIO (GLR)

4.1 Fault Detection and Confirmation Tests

In order to detect any abnormality, the following statistic measure which was first introduced in Narasimhan and Mah (1988), can be considered:

\[
\varepsilon(f; k) = \gamma^T(k)V^{-1}(k)\gamma(k) \tag{31}
\]

where \( V(k) \) is the covariance matrix of the residuals. This criterion which represents the weighted residuals, follows a central \( \chi^2 \) distribution with \( n \) degrees of freedom where \( n \) is the dimension of the innovation term \( \gamma \). A certain threshold can be set for this statistic which is known as fault detection test (FDT), and in case the test exceeds the predefined threshold then it is suspected that the fault has occurred. The occurrence of a fault could be confirmed by means of another statistic which is the accumulated version of the FDT test and is known as fault confirmation test (FCT). The FCT test uses the sum of FDT test in a specified window \([t, t+N]\) and is defined as follows (Narasimhan and Mah (1988)):

\[
\varepsilon(N; t) = \sum_{k=t}^{t+N} \gamma^T(k)V^{-1}(k)\gamma(k) \tag{32}
\]

The aforementioned statistic follows a central \( \chi^2 \) distribution with \( n \times (N + 1) \) degrees of freedom. Similarly, a certain threshold can be chosen for this criterion and the fault occurrence is confirmed when this threshold is exceeded.

The GLR test is defined as a double maximization over the fault that has occurred at time \( t \) and the magnitude of the fault \( b_{fj} \), where \( f \) and \( j \) represent the type and location of fault, respectively.

\[
\{\hat{b}_{fj}, \hat{t}\} = \arg \max_{b_{fj}, t} \frac{p(\gamma^N|t, b_{fj})}{p(\gamma^N)} \tag{33}
\]

where, \( \gamma^N = \{\gamma_1, \ldots, \gamma_N\} \), denotes the residuals in a specified window. In order to solve this optimization problem, it is further simplified by finding the estimated fault occurrence sample instant \( \hat{t} \) by means of the FDT and FCT tests. Thus, the problem reduces to a single optimization over the fault magnitude \( b_{fj} \). Since the detection of fault occurrence sample is undertaken by FDT and FCT tests, the GLR problem defined by (33), will be reduced to the followings:

\[
T_{fj} = \sup_{b_{fj}} \frac{p(\gamma^N|t, b_{fj})}{p(\gamma^N)} \tag{34}
\]

\[
\mathbf{T} = \max_{fj} T_{fj} \tag{35}
\]

where \( \gamma^N = \{\gamma_1, \ldots, \gamma_N\} \), \( \gamma_1, \ldots, \gamma_N \), and \( t \) is the time instant at which the fault has occurred.

Assuming the measurement noise to be additive and Gaussian,
the GLR problem can be further simplified to the minimization of the residuals over the FCT window (Deshpande et al. (2009)):

$$\min_{b_f} (J_f) = \sum_{k=N}^{t+N} \gamma_f(k)^T V_f(k)^{-1} \gamma_f(k)$$  \hspace{1cm} (36)$$

where $\gamma_f(k)$ and $V_f(k)$ are the innovation and the innovation covariance matrix, respectively, which are computed using the fault mode Kalman filter observer pertaining to fault $f_i$. It should be noted that in the case of dealing with multiple simultaneous faults, the Akaike information criterion should be used to isolate the occurred fault (Deshpande et al. (2009)).

5. SIMULATION RESULTS

Remark 4. As mentioned before, in order to detect fault occurrence, statistical tests such as FDT and FCT are used. For isolation purposes, after rejection of FDT and FCT tests, the fault mode Kalman filters are used to compute the residuals in the FCT window for each of the hypothesized faults. However, one of the most critical issues is selecting the size of FCT window. As a rule of thumb, in Prakash et al. (2002) it is suggested that the size of FCT window be chosen to be half the time required for the Kalman filter to converge after fault occurrence. It is also worth mentioning that, after the FCT is rejected, the covariance matrix of the errors in state estimates should be reset. This resetting will impose some delay on the fault isolation as it takes some time for the filter to converge. Furthermore, resetting the covariance matrix after any change in the control mode signal will significantly improve the performance of state estimation. In the current study, for the purpose of achieving more accurate isolation as well as low false alarm rate, the size of FCT window was selected to be 36 samples. All the results are summarized in Table 2.

5.1 Simulation Results for Faults in Pitch 1 ($\beta_1$)

The levels of significance for FDT and FCT tests of $\beta_1$ FDI module were set to 0.3 and 0.01, respectively. The high thresholds for FDT and FCT tests significantly reduced the number of false alarms. The average detected fault occurrence time for Fault 1 using the Monte Carlo simulations turned out to be 2000.01. Furthermore, the number of false alarms was found to be 10 over 100 simulations, just under 10%.

5.2 Simulation Results for Faults in Pitch 2 ($\beta_2$)

Despite the fact that Fault 6 has a week signature in comparison with the other faults, the levels of significance for FDT and FCT test were set equal to those of $\beta_1$. The average detected fault occurrence time instants for Fault 2 was found to be 2300.07 and average number of false alarms were 2 per each simulation. However, the average detected fault occurrence time instant of Fault 6 was 2950.38 which apparently cannot meet the specified requirements. The innovation sequence of $\beta_2$ estimator/FDI module in the time intervals of [2200 – 2500] and [2900 – 3000] are depicted in Figs.2 and 3 respectively. As shown in these figures, the residuals deviate immediately when Fault 2 occurs while in the presence of Fault 6, the residuals do not show any sign of deviation till time instant 2950.

5.3 Simulation Results for Faults in Pitch 3 ($\beta_3$)

The levels of significance for FDT and FCT tests were set equal to those of the $\beta_1$ and $\beta_2$ FDI modules. The average detected fault occurrence time instants for Faults 3 and 7 were found to be 2600.03 and 3402.17, respectively. It should be noted that the detection time for Fault 7 is far less than the specified requirements. The average number of false alarms was equal to 1 per each simulation. Fig. 4 depicts the performance of state estimation module of pitch 3 after detection and isolation of Fault 3 and switching to its relevant fault mode observer.

Remark 5. Despite the fact that faults related to $\beta_1$, $\beta_2$ and $\beta_3$ are different in terms of strength, the levels of significance of
FDT and FCT tests for all pitch systems are set to the same values.

5.4 Simulation Results for Faults in Converter ($\tau_g$)

The levels of significance for FDT and FCT tests were set to 0.1 and 0.01, respectively. The average detected fault occurrence time instant for Fault 8 turned out to be 3800.02 while the number of false alarms was 20 per 100 simulations.

5.5 Simulation Results for Faults in Drive Train module ($\omega_r$ and $\alpha_b$)

The levels of significance for FDT and FCT tests were both set to 0.01. It should be noted that Faults 4 and 5 strongly cause the deviation of the residuals from being white and consequently the thresholds for FDT and FCT tests were selected to be as high as possible. The average detected fault occurrence time instants for Fault 4 and 5 were computed as 1000.04 and 1500.10, respectively. The number of false alarms in this case was 14 per 100 simulations. The performance of the AR model proposed for denoising the wind speed is shown in Fig. 5.

![Fig. 5. Denoising the wind speed measurement](image)

**Remark 6.** Regarding actuator faults (Fault 6 and 7), it should be mentioned that in order to achieve more accurate results in case of high uncertainty in model parameters, methods such as marginalized likelihood ratio (MLR) should be used (Kiasi et al. (2010)).

The results of Monte Carlo simulations performed to assess the performance of the FDI system for all faults are summarized in table 2.

<table>
<thead>
<tr>
<th>Subsystem</th>
<th>Filter Type</th>
<th>Fault Type</th>
<th>FDT/FCT Level of Significance</th>
<th>False Alarm</th>
<th>Fault Occurrence</th>
<th>Detected Fault Occurrence Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>KF</td>
<td>Sensor $P_1$</td>
<td>0.3/0.01</td>
<td>2/each run $^a$</td>
<td>1200</td>
<td>1200 01</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>KF</td>
<td>Sensor $P_2$</td>
<td>0.3/0.01</td>
<td>2/each run $^a$</td>
<td>2500</td>
<td>2500 02</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>Activated P</td>
<td>0.3/0.01</td>
<td>2/each run $^a$</td>
<td>2500</td>
<td>2500 03</td>
<td></td>
</tr>
<tr>
<td>$\lambda_1$</td>
<td>KF</td>
<td>Sensor $F_1$</td>
<td>0.3/0.01</td>
<td>2/each run $^a$</td>
<td>1000</td>
<td>1000 01</td>
</tr>
<tr>
<td>$\alpha_b/\alpha_y$</td>
<td>UKF</td>
<td>Sensor $P_2$</td>
<td>0.01/0.01</td>
<td>1/each run $^a$</td>
<td>1000</td>
<td>1000 01</td>
</tr>
</tbody>
</table>

$^a$ Each standard run is 4400 seconds as per models provided by Odgaard et al. (2009).

6. CONCLUDING REMARKS

In this paper the the GLR method along with the statistical FDT and FCT tests was used to detect and isolate the faults of the wind turbine benchmark problem. The fault detection and isolation module of the pitch system was split into three separate parts corresponding to $\beta_1$, $\beta_2$ and $\beta_3$. Each FDI module in this system was designed based on a linear Kalman filter with correlated process and measurement noise to estimate the states. The results of the simulations proved to be consistent and complied with requirements of the problem except for Fault 6. The FDI module of the converter system was designed using a simple linear Kalman filter and the simulation results were within the specifications of the benchmark problem. It should be noted that the converter FDI module is also stand-alone and independent of the other FDI modules. However, the generator FDI system which is not addressed in this work should be working in series with all other subsystems.

The state estimation of the drive train system which has a highly nonlinear model was performed using the UKF and the simulation results were acceptable. However, the level of uncertainty is very high in the drive train system due to the accumulated errors pertaining to the noisy measurement of wind speed as well as errors in estimation of the pitch angles. Finally, the fact that the FDI module of the drive train is a function of the pitch angles as well as the wind speed, makes it a dependent system and consequently it should be working in series with the other modules. In order to avoid false alarms and misclassifications in the drive train fault detection system, it is recommended that upon detection of faults in each of the pitch modules, the FDI system of the drive train be disabled.

REFERENCES


