Sensor Fault Detection and Isolation of Modern Wind Turbines

Essam Nabil*, Abdul-Azim Sobaih, Belal Abou-Zalam

Department of Industrial Electronics and Control Engineering, Faculty of Electronic Engineering, Minoufia University, Minouf, Egypt

Email address
essam.abdelaziz@el-eng.menofia.edu.eg (E. Nabil)

*Corresponding author

Citation

Abstract
Reliability, survivability, cost efficiency and high performance are required for modern wind turbines to be competitive within the renewable energy market. In this paper, an integrated fault detection and isolation (FDI) system is designed to detect sensor fault scenarios of the benchmark model of horizontal-axis standard modern wind turbines. The developed FDI technique is proposed utilizing a reconfigurable constrained discrete Kalman filter algorithm. After detecting and isolating the faulty sensor, the sensor effectiveness factor for the faulty system is then estimated in the existence of model disturbances as well as measurement random noise. Simulation result on a 4.8 Mega Watt, variable pitch and variable speed horizontal axis modern wind turbine (HAWT) dynamic model to justify the validation of the proposed design scheme.

1. Introduction

Wind energy has the fastest growth rate as a renewable energy resource and technology all over the world recently. The usage of modern wind turbines is the most cost-effective renewable resources [1]. Clearly, the aerodynamics of modern HAWT remain a challenging crucial research area and topics for wind energy. A planned service of wind turbines is essential demand to be cost-competitive, because the turbines are usually installed offshore. It would be beneficial to develop fault detection and diagnosis schemes with early detection of catastrophic faults deteriorating other parts of the wind turbine, and decrease possible maintenance costs. The considered benchmark modern wind turbine model in this paper presents numerous different individual sensor faults, in which fault detection, isolation, estimation and accommodation necessities and requirements are described [2]. Among others, rotor and generator speed measurement faults are dealt with in it and the measurement of converter torque. Earlier investigations of literature employ observer-based FDI scheme for sensor faults of wind turbines [3, 4, 5, 10]. A usage of the unknown input observer based detection and isolation schemes can be seen in [7, 8]. In [9], a fault detection and isolation technique with minimized human operating assumptions and decisions requirement is proposed utilizing a generic automated design technique. Related numerous algorithms and schemes for FDI and fault accommodation of modern wind turbines is presented in [6]. A constrained Kalman filters based FDI technique is developed in this paper by for fault detection and diagnosis of sensor faults of modern wind turbines. The design procedures imply: (1) an integrated design of FDI scheme using a bank of constrained reconfigurable Kalman filters, (2) an obvious fault estimation algorithms are derived that can estimate the effectiveness factor of a detected faulty sensor with existence of the simulated system disturbance and measurement noise.
This paper is organized as follows. In Sect. II, the wind turbine plant model description is introduced. The description of the proposed FDD design strategy for considered HAWT is presented in Sect. III. Section IV presents the simulation results followed by the conclusions and the list of relevant references.

2. System Model Description

2.1. Modern Wind Turbine Plant

The considered wind turbine model description is a three-bladed rotor modern variable pitch and variable speed HAWT with a functional yaw system to keep the rotor orientation upwind [2]. The main target of controlling the wind turbines is to maximize the generated electric power and minimize the operational cost. Modern wind turbines operate according to a typical power curve as demonstrated in Figure 1.

![Figure 1. Typical power curve of a controlled variable pitch and variable speed HAWT.](image)

No electrical energy is produced from the turbine at levels below the cut-in limit of effective wind speed, \( V_{w,\text{cut-in}} \), since the effective cost surpasses the income produced power. The wind turbine generates an electric power in a finite operational range of effective wind speeds only, which is further partitioned into two different control regions, the partial load region denoted as I and the full load region denoted as II. In the partial load region extended from \( V_{w,\text{cut-in}} \) to the rated effective wind speed, \( V_{w,N} \), the torque control as well as pitch control are applied to generate as much power as possible through maximizing the operational efficiency of the rotor aerodynamics. Operation in the full load region extended from \( V_{w,N} \) to the cut-out level of speed, \( V_{w,\text{cut-out}} \), illustrates that the generated electrical power is saturated at a rated level for minimizing the structural and functional loads and eliminate fatigue damages. At wind speeds higher than cut-out level, the turbine is forced to shut down for protecting it from catastrophic structural and functional overloads. The drive train principle diagram of HAWT model is illustrated in Figure 2.

![Figure 2. Wind turbine drive train principle diagram.](image)

The continuous time aerodynamic sub-system model can be estimated relying on the estimated reference wind speed input sequence i.e. \( v_r(t) \), operational pitch angle of the rotor blades i.e. \( \beta(t) \) and the rotational rotor speed i.e. \( \omega_r(t) \) as:

\[
T_g(t) = \frac{1}{2}\rho \ A \ \omega_r^2(t) \ C_p(\lambda(t), \beta(t))
\]

Where \( \rho \) represents the air density, \( A \) defines the profile area of the rotor blades, \( \beta(t) \) is the operational pitch angle, \( \lambda(t) \) represents the operational tip speed ratio TSR. The drive train model can be represented using a simple mechanical one body model as:

\[
J_r \dot{\omega}_r(t) = T_e(t) - K_{\text{at}} \Delta(t) - (B_{\text{at}} + B_r) \omega_r(t) + \frac{\eta_{\text{dt}}}{N_g} \omega_g(t)
\]

\[
J_g \dot{\omega}_g(t) = \frac{\eta_{\text{gt}}}{N_g} \Delta(t) + \frac{\eta_{\text{gt}}}{N_g} B_r \omega_r(t) - \left( \frac{\eta_{\text{gt}}}{N_g} B_{\text{at}} + B_g \right) \omega_g(t) - T_g(t)
\]

\[
\dot{\theta}_\Delta(t) = \omega_r(t) - \frac{1}{N_g} \omega_g(t)
\]

Where \( T_{\text{g,ref}}(t) \) represents the reference torque of the power generator, \( \tau_{g,d} \) defines the time delay of the power converter model while \( \tau_g \) defines the generator model time constant. The generated power produced by the converter is calculated from:

\[
P_{g}(t) = \eta_g \ \omega_g(t) \ T_g(t)
\]

Where \( P_{g}(t) \) is the power produced by the generator, and \( \eta_g \) is the efficiency of the generator. The state space benchmark model can be described as:
\[ \dot{x} = A_c x + B_c u \]  
\[ y = C_c x \]  

where \( A_c \) defines the system parameters matrix, \( x \) represents the independent state vector of the first order system equations, \( B_c \) defines the system input control matrix while \( u \) represents the control vector, \( C_c \) defines the measurement output matrix and \( y \) represents the system output vector. The continuous-time model parameters are given as:

\[
A_c = 
\begin{bmatrix}
-B_{dth} + B_{d} & -K_{dth} & 0 \\
-\eta_d B_{dth} N_g g & -\eta_d B_{d} N_g g & -1 \\
1 - 1/N_g & 0 & 0 \\
0 & 0 & 0 \\
\end{bmatrix} \]

\[
B_c = \begin{bmatrix}
1
0
0
0
\end{bmatrix},
\]

The conducted model parameters of a 4.8 Mega Watt, variable pitch and variable speed horizontal-axis modern wind turbine (HAWT) model are listed in table 1 [2].

### Table 1. The model parameters of the wind turbine plant.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( A )</td>
<td>10.387 m²</td>
</tr>
<tr>
<td>( P )</td>
<td>1.225 kg/m²</td>
</tr>
<tr>
<td>( B_t )</td>
<td>7.11 Nm/(rad/s)</td>
</tr>
<tr>
<td>( B_a )</td>
<td>45.6 Nm/(rad/s)</td>
</tr>
<tr>
<td>( J_r )</td>
<td>55<em>10^6 Kg</em>m²</td>
</tr>
<tr>
<td>( J_g )</td>
<td>390 Kg*m²</td>
</tr>
<tr>
<td>( \eta_a )</td>
<td>95</td>
</tr>
<tr>
<td>( \tau_g )</td>
<td>20 ms</td>
</tr>
<tr>
<td>( \eta_b )</td>
<td>0.97</td>
</tr>
</tbody>
</table>

A subsequent discrete state space model representation which is obtained based on that continuous-time model parameters can be written as:

\[
x_{k+1} = A x_k + B u_k + w_k 
\]

\[
y_k = C x_k + v_k
\]

\( A, B \) and \( C \) indicate the corresponding discrete system matrices, \( w_k \) is the system disturbances, and \( v_k \) represents the zero mean measurement stochastic noise.

### 2.2. Modeling Sensor Faults

The output equation of the post-fault system model with individual measurement sensor faults is represented as [11, 12]:

\[
y_k = C_f x_k + v_k
\]

Where \( C_f \) represents the measurement output matrix with sensor faults and can be defined by:

\[
C_f = (1 - r_{c}) C
\]

\[
r_{c} = \text{diag}(y_{s1}, y_{s2}, \ldots, y_{sn})
\]

The independent state vector of the first order system equations, \( B_{c} \) defines the system input control matrix while \( u \) represents the control vector, \( C_{c} \) defines the measurement output matrix and \( y \) represents the system output vector. The continuous-time model parameters are given as:

\[
A_{c} = 
\begin{bmatrix}
-B_{dth} + B_{d} & -K_{dth} & 0 \\
-\eta_d B_{dth} N_g g & -\eta_d B_{d} N_g g & -1 \\
1 - 1/N_g & 0 & 0 \\
0 & 0 & 0 \\
\end{bmatrix}
\]

\[
B_{c} = \begin{bmatrix}
1
0
0
0
\end{bmatrix},
\]

where \( y_{si} \) represents the faulty sensor effectiveness factors indicating the measurement faults of the output equation. If \( y_{si} = 0 \) that indicates no fault or fault-free case. If \( 0 < y_{si} < 1 \) that indicates partial measurement fault occurrence. If \( y_{si} = 1 \) that refers to a complete sensor measurement failure occurs or malfunction.

### 3. Sensor Fault Detection and Isolation Algorithm

The developed FDI scheme is introduced in this section utilizing a reconfigurable constrained Kalman filters [11]. Isolation of the individual sensor fault is performed through generating constrained structured residual signals. The residual signals must be sensitive to specific sensor faults but unconscious to others through dividing the measurement matrix \( C \) into distinct pair of constrained matrices i.e. \( C_{incl} \) and \( C_{excl} \). Thereby the system output vector i.e. \( y_k \) will be divided to \( y_{incl} \) and \( y_{excl} \) respectively. The system state space model of equation (10) becomes:

\[
y_k = [y_{incl}(k)\, y_{excl}(k)] = [C_{incl}(k)\, C_{excl}(k)] x_k + v_k
\]

where \( C_{incl} \) and \( C_{excl} \) for the \( i \)th sensor are given as:

\[
C_{incl} = \begin{bmatrix}
C_{i1} & C_{i2} & \cdots & C_{in} \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & 0 \\
\end{bmatrix}
\]

\[
C_{excl} = \begin{bmatrix}
C_{i1} & C_{i2} & \cdots & C_{in} \\
\vdots & \vdots & \ddots & \vdots \\
C_{(i-1)1} & C_{(i-1)2} & \cdots & C_{(i-1)n} \\
0 & 0 & \cdots & 0 \\
\end{bmatrix}
\]

The discrete prediction (time update) and correction (measurement update) equations of reconfigurable Kalman filter algorithm are written as:

\[
\hat{x}_{k+1/k} = A \hat{x}_{k/k} + B u_k
\]
\[
\dot{x}_{k+1/k} = A \dot{x}_{k+1/k} + g [y_{k+1} - C \dot{x}_{k+1/k}]
\]  
(15)

Where \( g \) defines the innovation updating gain matrix of the estimator chosen to provide a decayed response of the generated estimation error \( e_k \) where:

\[
e_k = x_k + \dot{x}_{k/k}
\]  
(16)

\[
e_{k+1} = x_{k+1} + \dot{x}_{k+1/k+1}
\]  
(17)

Substituting with equations (9) and (15) into equation (17) we have:

\[
e_{k+1} = (I - g C) A e_k + (I - g C) w_k - g v_k
\]  
(18)

The error covariance i.e. \( \sum_{ee}(k+1) \) by squaring both sides of equation (18) and then taking the stochastic mean is obtained as:

\[
\sum_{ee}(k+1) = (I - g C) A \sum_{ee}(k) A^T (I - g C)^T + (I - g C) \sum_{ww} (I - g C)^T - g \sum_{vv} g^T
\]  
(19)

where \( \sum_{ww} \) and \( \sum_{vv} \) represent the individual disturbance and measurement noise covariance respectively. The discrete prediction (time update) and correction (measurement update) equations of reconfigurable Kalman filter algorithm for equation (13) is written as:

\[
\sum_{ee}(k+1) = (I - g c_{incl}) A \sum_{ee}(k) A^T (I - g c_{incl})^T + (I - g c_{incl}) \sum_{ww} (I - g c_{incl})^T - g \sum_{vv} g^T
\]  
(20)

Solving for \( g \) as well as the error covariance i.e. \( \sum_{ee} \) by taking the first order variance of equation (22). Hereby, FDI is dependent on obtaining \( \bar{e}_k \) that should be null or close to zero for fault free case depending on the individual system disturbances and measurement noise but will be considerably high for the faulty case. A reconfigurable constraint discrete Kalman filter estimator is designed for each individual group of measurement sensors and for each separated. Fault isolation is achieved by fault detection of the faulty group, and the included single faulty sensor within the previous detected group subsequently.

### 4. Sensor Fault Estimation Algorithm

Estimating the sensor effectiveness factor i.e. \( y_{si} \) for the \( i \)-th sensor in equation (12) for the faulty system is referred as fault estimation. After the sensor fault occurrence, the output measurement sensor matrix i.e. \( C \) will be changed from:

\[
\hat{x}_{k+1/k} = \hat{x}_{k+1/k} + g [C_f x_{k+1} + v_k - C \hat{x}_{k+1/k}]
\]  
(25)

The discrete prediction (time update) and correction (measurement update) equations of reconfigurable Kalman filter algorithm of equations (14), (15) will become:

\[
\hat{x}_{k+1/k+1} = \hat{x}_{k+1/k} + (I - g C) \hat{x}_{k+1/k} + g C_f x_{k+1} + g v_k
\]  
(26)

Substituting with equations (9) and (14) we obtain:

\[
\hat{x}_{k+1/k+1} = (I - g C) \hat{x}_{k+1/k} + g C_f x_{k+1} + g v_k
\]  
(27)

and equation (18) will be:

\[
e_{k+1} = -(I - g C) A e_k + g D C x_{k+1} + (I - g C) w_k - g v_k
\]  
(28)

with \( D C = C - C_f = [0, \ldots, y_{si}, \ldots, 0]^T \), \( i = 1, 2, \ldots, q \)

The state estimation error covariance of equation (22) will be written considering \( i \)-th sensor fault as:

\[
\sum_{ee}(k+1) = (I - g C) A \sum_{ee}(k) A^T (I - g C)^T + g \Delta C \sum_{xx} C \Delta C^T g^T + (I - g C) \sum_{ww} (I - g C)^T + g \sum_{vv} g^T
\]  
(29)

where \( \sum_{xx} \) expectation is obtained as:

\[
\sum_{xx} = E \{ x_{k+1} x_{k+1}^T \}
\]  
(30)

from (22) and (29) we have:

\[
\Delta \sum = \sum_{ee} - \sum_{ee} + g \Delta C \sum_{xx} C \Delta C^T g^T
\]  
(31)

Let \( \Delta C = y_{si} \beta_s \) and \( M_s = g \Delta C \sum_{xx} C \Delta C^T g^T \)

Then we can write:

\[
M_s = y_{si}^2 (g \beta_s \sum_{xx} \beta_s^T g^T) = y_{si}^2 \Theta_s
\]  
(32)

\[
\Theta_s = g \beta_s \sum_{xx} \beta_s^T g^T
\]  
(33)
Rearranging the non-zero elements of the matrix $M_s$ as well as the non-zero elements of $\Theta_s$, corresponding to those of $M_{sk}$ and $\Theta_{sk}$ respectively, $\gamma_{si}$ can be estimated as a mean value of a number of rearranged non-zero elements i.e. $N_s$ as:

$$
\gamma_{si} = \frac{1}{N_s} \sum_{k=1}^{N_s} \sqrt{\frac{M_{sk}}{\Theta_{sk}}} \quad (34)
$$

5. Simulation Results

Simulation results are conducted a wind input sequence shown in figure 3. The operational pitch angles and tip speed ratio of the aerodynamic rotor blades are shown in figure 4 and 5 respectively. The appropriate estimated aerodynamic torque and the generator torque reference signals are shown in figure 6 and 7 respectively. The first fault scenario is simulated as a partial sensor fault with effectiveness factor of 0.66 introduced at the time instants of 500 seconds for the second sensor only i.e. the generator speed sensor. The simulation results in figures 8, 9 and 10 demonstrate the system outputs response for fault-free case and faulty response case. Figure 11 shows the constrained Kalman Filter estimator performance by representing the responses of both real system states and estimated system states. As shown in the produced responses, the estimator for the second sensor has detected a fault at the time instants of 5 seconds but the estimators for other sensors haven't detected any faults and that is declared through the generated residual signals shown in figure 12, 13 and 14 respectively. The produced residual signals belongs to the rotor speed measurement sensor and the generator torque measurement sensor are close to zero but the residual signal of the generator speed sensor considerably high due to the faulty sensor effect. After fault detection and isolation (FDI) technique has finished its role by detecting the faulty component(s) and isolating it from other system components, fault estimation algorithm is activated consequently to identify the seriousness of the detected fault through estimating the related effectiveness factor. Through the introduced fault estimation algorithm, the last estimate of the effectiveness factor i.e. $\gamma_2$ is 0.6588 that is precisely close to the assumed simulated value of the fault scenario.

![Figure 3. Wind speed input sequence.](image)

![Figure 4. Operational pitch angles.](image)

![Figure 5. Operational tip speed ratio (TSR).](image)
Figure 6. The estimated aerodynamic torque.

Figure 7. The generator torque reference.

Figure 8. The rotor speed output response.

Figure 9. The generator speed output response.

Figure 10. The generator torque output response.

a. Performance for x1 and x2
The second fault scenario is simulated as a partial multiple sensor faults with effectiveness factors of 0.45 and 0.35 introduced at the time instants of 500 seconds for the first and third sensors respectively. The system outputs response for fault-free case and faulty response case are demonstrated in figure 15, 16 and 17. The residual signals are shown in figures 18, 19 and 20. As well as, the constrained Kalman Filter estimator performance for this case is illustrated in figure 21. The last estimate of the effectiveness factor for the rotor speed measurement sensor is 0.0.4478 and for the generator torque measurement is 0.0.3477 that close to the simulated values of the fault scenario. All these provided results confirm the effectiveness of the developed fault detection and diagnosis (FDD) mechanism; also the proposed fault isolation algorithm that inherently embodied into the detection stage by using grouped constrained Kalman filters provides a computation load reduction for large number of sensors.
Figure 15. The rotor speed output response.

Figure 16. The generator speed output response.

Figure 17. The generator torque output response.

Figure 18. The Residual for the rotor speed.

Figure 19. The Residual for the generator speed.

Figure 20. The Residual for the generator torque.
6. Conclusion

The integrated sensor FDI scheme proposed in this paper possesses employing analytical redundancy by utilizing a set of reconfigurable constrained discrete Kalman filters. The proposed technique detects different sensor fault scenarios of the benchmark model of horizontal-axis standard modern wind turbines with a short and acceptable time period as both fault detection and isolation processes are performed simultaneously, and a computation load reduction for large number of sensors. An explicit fault estimation algorithms are derived that can estimate the effectiveness factor of a detected faulty sensor in spite of including simulated system disturbances and random measurement noise.

References


