Simulation Study of Fault Detection and Diagnosis for Wind Turbine System

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Abstract—This paper presents a quantitative review of early detection and estimation of fault for wind turbine system. The model-based technique is proposed to provide an assessment of all possible faults for renewable energy sources. The augmented observer is applied to estimate the real physical data of the system sensor faults and states simultaneously. The fault detection and diagnosis is designed to be most sensitive to faults and states of wind turbine system. A mathematical example is specified to exhibit the dynamic system behavior for the wind turbine model to validate the competence of the system performance. The state space is used to explain the design. The satisfactory fault diagnosis performance is demonstrated in the simulation results.

Keywords—Condition monitoring, fault detection, fault diagnosis, augmented observer, fault estimation, wind turbine.

I. INTRODUCTION

Over the past two decades, wind energy has become a useful vital renewable energy source. Since 1970s, many researchers have been concentrating on fault detection in wind turbines. Wind turbine (WT) is one of the fastest growing and promising emergent sources of electrical energy in today’s economy and future renewable energies. The costs of operations and maintenance of wind turbines is relatively high compared to the building of the turbine itself. Monitoring the system is no longer sufficient to diagnose all faults, which is one of the additional challenges faced by the Wind industry. Researchers have suggested different kind of methods of observing various faults in wind turbines[1]. This has instigated a lot of studies in this field, the purpose of which is to investigate components failure rate and consider the nature of their fault[2]. However, wind turbine energy generation has had challenges over the years because of ineffective system monitoring and poor reliability[3]. Unexpected faults or failures due to component degradation in wind turbines can lead to substantial damage in the system[3]. Fault detector practice is used to identify whether faults have occurred in a system or not and to make it possible to identify faults[4]. A “fault” could be an unexpected change of a system’s function, which might cause abnormal working operation of the system performance. However, might not necessarily lead to physical system breakdown. It is essential to detect faults in a system on time in order to avoid individual, entire or partial system unit down time or prevent serious damage to the turbine. Fault diagnosis (FD) is a monitoring system that can control the system system’s performance as well as provide possible information on any irregular working parts of the system.

The distribution downtime per component parameter of failure rate as recorded in 2000-2004 in Sweden represents a catastrophic failure level of electric system sensors and blade/pitch components as shown below in Fig. 1, [3].

![Fig. 1. The amount of failures for Swedish wind turbines between 2000-2004](image)

This paper is structured as follows. Observer based fault detection and diagnosis (FDD) is discussed in section II, state space of WT model is described and discussed in III and IV, detailed simulation result analysis, brief conclusion as well as future work will be presented in section V.

II. OBSERVER BASED SCHEME

An observer is a dynamical system that uses available input and output measurements to provide estimates of state variables that are not available to be measured in the system. The normal plant system is represented by equation (1), therefore the dynamic state-space plant model is defined as
\[
\begin{align*}
\dot{x}(t) &= Ax(t) + Bu(t) \\
y(t) &= Cx(t) + Du(t)
\end{align*}
\] (1)

Where \( x(t) \in \mathbb{R}^n \), \( u(t) \in \mathbb{R}^m \) and \( y(t) \in \mathbb{R}^p \) represents \( x \) as state of the system, \( u \) is the input of the system and \( y \) is output of the system in dimensions of \( n, p \) and \( m \). \( A, B, C \) and \( D \) are known matrices with appropriate dimensions.

The mathematical description of an observer is defined as:

\[
\begin{align*}
\dot{\hat{x}}(t) &= A\hat{x}(t) + Bu(t) + K[y(t) - \hat{y}(t)] \\
\dot{\hat{y}}(t) &= C\hat{x}(t) + Du(t)
\end{align*}
\] (2)

The difference between \( y(t) \) and estimation of \( \hat{y}(t) \) is the system vector error. Hence the dynamic error used to achieve desired accuracy of the system can be written as:

\[
\dot{\varepsilon} = \hat{y}(t) - \hat{y}(t) = (A - KC)\varepsilon(t)
\] (3)

Where ‘\( K \)’ is detectable which represents observer gain to be designed with the aim of constantly correcting the systems output and improving state estimates \([4, 5]\). The gain observer function is used to increase the system stability as well as the accuracy of system estimation. The current error which is the difference between the desired current output and measured current output as discussed in \([6]\) will give precise error accuracy.

Fault detection is based on generating a signal and comparing the physical measurements provided by the associated system model \([7, 8]\). There is a need to develop an effective method for detecting and diagnosing all possible faults in wind turbine system. The system with faults can be defined as shown in Fig 2.

![Fig. 2. Faults in the controlled wind turbine system](image)

**III. STATE SPACE OF WIND TURBINE MODEL**

The main components of the 5MW wind turbine system, is defined at a wind speed of 10m/s demonstrated in linear state space matrices as shown in the table below. Table I gives a narrative report of the wind turbine chosen parameters such that it represents a realistic output of real world data for a wind turbine \([9]\).

**Table I. Report of Parameters for Wind Turbine Systems**

<table>
<thead>
<tr>
<th>DESCRIPTION</th>
<th>SYMBOL</th>
<th>DESCRIPTION</th>
<th>SYMBOL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turbine Inertia</td>
<td>( J_f )</td>
<td>Leakage coefficient</td>
<td>( \sigma )</td>
</tr>
<tr>
<td>Gearbox ratio</td>
<td>( n_g )</td>
<td>Stator current</td>
<td>( i_d, i_q )</td>
</tr>
<tr>
<td>Generator inertia</td>
<td>( J_G )</td>
<td>Pitch angle</td>
<td>( \beta )</td>
</tr>
<tr>
<td>Torsional stiffness</td>
<td>( K_s )</td>
<td>Desired pitch angle</td>
<td>( \beta_d )</td>
</tr>
<tr>
<td>Torsional damping</td>
<td>( C_s )</td>
<td>Mechanical torque</td>
<td>( T_{wt} )</td>
</tr>
<tr>
<td>Synchronous speed</td>
<td>( \omega_s )</td>
<td>Electrical torque</td>
<td>( T_e )</td>
</tr>
<tr>
<td>Stator resistance</td>
<td>( R_s )</td>
<td>Control torque</td>
<td>( T_e )</td>
</tr>
<tr>
<td>Rotor resistance</td>
<td>( R_r )</td>
<td>Control rotor voltages</td>
<td>( V_{dr}, V_{qr} )</td>
</tr>
<tr>
<td>Stator inductance</td>
<td>( L_s )</td>
<td>Wind turbine speed</td>
<td>( \omega_{wt} )</td>
</tr>
<tr>
<td>Rotor inductance</td>
<td>( L_s )</td>
<td>Generator speed</td>
<td>( \omega_m )</td>
</tr>
<tr>
<td>Mutual inductance</td>
<td>( L_m )</td>
<td>Stator voltage</td>
<td>( V_s )</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Gearbox ratio</td>
<td>( n_p )</td>
</tr>
</tbody>
</table>

\( A \). Description theory of wind turbine

Wind turbine scheme comprises the aerodynamics (which is the power output determined by the wind speed), mechanical drive train and the electrical operational characteristic of the generator\([2, 6, 10-14]\).

These chosen parameters represent wind turbine model when an induction motor operates as a generator and is interpreted as follows: State of the system of which \( \beta \) denotes the pitch angle, \( \theta_K \) represents the angular speed position of torsional stiffness of the shaft, \( \omega_{wt} \) is wind turbine speed, \( \omega_m \) corresponds to generator speed, \( i_d \) is d-axis rotor current and \( i_q \) indicates q-axis rotor which is the current flowing into the rotor side converter (RSC) according to rotating reference frame.

Some input parameters are \( T_{wt} \) which represents wind turbine torque, \( T_e \) characterizes the electrical control torque, \( V_o \) is the active control rotor voltages and \( V_e \) is the reactive control voltages.

Output parameter comprises of \( T_e \) which is electromagnetic torque generated by the machine and other components already defined in the state system.

The State space mathematical representation of a wind turbine model in a linear system with fault can be denoted as:-
The system is defined in a continuous linear state space
Where, \( f(t) \in \mathbb{R}^k \) is the fault system, thus, \( k \) is designated as state of fault.

\[
x, u \text{ and } y \text{ are defined as the following parameters used as explained above:}
\]

\[
x = \begin{bmatrix} \beta, \theta_K, \omega_w, \omega_m, i_{dr}, T_{gr} \end{bmatrix}^T
\tag{5}
\]

\[
u = \begin{bmatrix} \beta_T, \theta_{wT}, \omega_{wT}, \omega_{mT}, v_{dr}, v_{qr} \end{bmatrix}^T
\tag{6}
\]

\[
y = \begin{bmatrix} \beta, \omega_w, \omega_m, T_e \end{bmatrix}^T
\tag{7}
\]

In general, for ramp fault and abrupt (step) faults can be verified in a real world data, of which the second-order derivative of the fault must be zero. Hence, it is specified as \( \dot{f} = \ddot{f} = 0 \) [15]. Hence, the dynamic system can be a wind turbine system or any other system. If there are faults in the system, there is a need to develop effective methods for distinguishing the fault.

Illustrating the dynamic system model parameters in matrices state space as:

\[
A = \begin{bmatrix}
-1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \frac{1}{\sigma_L} & 0 & 0 & 0 \\
0 & k_1 & \frac{-C_I}{J_f} & k_1 & 0 & 0 \\
0 & k_2 & k_3 & \frac{-\beta}{\sigma_L} & k_3 & 0 \\
0 & 0 & 0 & \frac{-\beta}{\sigma_L} & k_4 & 0 \\
0 & 0 & 0 & 0 & \frac{-\beta}{\sigma_L} & k_5 \\
\end{bmatrix},
\]

\[
B_f = \begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 \\
\end{bmatrix}
\]

\[
D_f = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
\end{bmatrix}
\]

Where \( D = \) zeros matrix, \( k_1 = \frac{C_s}{J_F n_g}, k_2 = \frac{K_s}{J_G n_g}, \)

\[
k_3 = \frac{C_s}{J_G n_g}, k_4 = -\frac{C_s}{J_G n_g}, k_5 = \omega_w - \omega_m,
\]

\[
k_6 = \frac{(i_d + L_m V_s q)}{L_s \omega_s}, \quad k_7 = -\sqrt{3} n_p L_m V_s K_c / \omega_L.
\]

\[
\theta = \omega_w - \omega_m / n_g, K_c = 0.8383
\]

Suppose sensor faults are in the following forms:

\[
f_{s, \text{step}} = \begin{cases}
1, & t \geq t_1 \\
0, & t < t_1
\end{cases}
\tag{8}
\]

\[
f_{s, \text{ramp}} = \begin{cases}
-0.04t, & t \geq t_2 \\
0, & t < t_2
\end{cases}
\tag{9}
\]

Faults are in the successive forms as \( f = f_s \).

\subsection{B. Implementation of Augmented Observer}

Outlining the state system of the improved plant with fault augmented observer will aim to provide estimates of the state and the fault at the same time using available input and output.

\[
\tilde{x} = \begin{bmatrix} \tilde{x}_1 & \tilde{x}_2 & \tilde{x}_3 & \tilde{x}_4 & \tilde{x}_5 \end{bmatrix}^T \in \mathbb{R}^5
\tag{10}
\]

An augmented state-space plant system can be simplified according to [16] as follows:

\[
\dot{\tilde{x}} = \tilde{A} \tilde{x} + B \tilde{f} + \tilde{B}_f f
\]

\[
y(t) = C \tilde{x}(t) + Du(t)
\]

\[
\tilde{n} = n + k \times 2
\]

\[
\tilde{A} = \begin{bmatrix}
A & 0 & \cdots & 0 & B_f \\
0 & 0 & \cdots & 0 & 0 \end{bmatrix} \in \mathbb{R}^{5 \times 5}
\]

\[
\tilde{B} = \begin{bmatrix}
0 & 0 & \cdots & 0 & 0 \\
0 & 0 & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \cdots & 0 & 1 \\
0 & 0 & \cdots & 0 & 1
\end{bmatrix}
\]
The estimation error dynamic is defined as
\[
\tilde{e} = \tilde{x} - \hat{x}
\]
(14)

So augmented observer gain \( \hat{K} \) is chosen such that the eigenvalues of the matrix \((\hat{A} - \hat{K}C)\) is stable.

The observability condition to make the error dynamics \( \tilde{e} = (\hat{A} - \hat{K}C)\tilde{e} \) is to limit its response behavior.

Applying augmented design techniques [16] to wind turbine will establish the estimates of state and fault as follows:
\[
\begin{bmatrix}
\hat{x} \\
\hat{f}
\end{bmatrix} =
\begin{bmatrix}
I_{n_x,n} & 0_{n_x,k} & 0_{n_x,k}
0_{k_x,n} & I_{k_x,k} & 0_{k_x,k}
0_{k_x,k} & 0_{k_x,k} & I_{k_x,k}
\end{bmatrix}
\begin{bmatrix}
\tilde{x} \\
\tilde{f}
\end{bmatrix}
\]
(16)

The model-based diagnosis technique is a method of fault diagnosis which gives estimation of all possible faults in the system.

IV. SIMULATION RESULTS AND ANALYSIS

The simulation results shown below demonstrate two types of fault events which are: step (abrupt) and ramp fault that often occurs in practical real world systems and can give information about any other faults in the system. However, they are realistic in providing more information about all possible faults. There are two cases to be investigated in this model. Case 1 examined fault diagnosis while case 2 describes the error difference between the real system state and its estimated response in the system. Firstly, Fig. 3, to Fig. 10 demonstrates a response to step change in sensor fault at zero initial condition in addition, the ramp signal diagnosed appropriate information of its accurate estimate that is promising for practical application. It is observed from the results that fault occur in the system that exhibits the systemic response as stated in equation (8) and (9). The step time is displayed as \( t_s \) and ramp time to be \( t_r \) as demonstrated in the fig. below estimating all sensor faults respectively. All real sensor faults are indicated in red solid lines and their estimated signal is in blue dash lines that clearly describe the system’s behaviour response. The augmented observer has successfully tracked other faults affected in the system, convergence are desirable which demonstrates its sensitivity of real world system performance response.
Secondly, case 2 illustrates the augmented observer as a precise dynamic state error estimator just that the behaviour of the fault is asymptotically stable. The difference between the state system and its estimated state system is defined as the state dynamic error vector which predicts the behaviour of the wind turbines. Fig. 11, to Fig. 16, represents the error between the real state system and its estimated state system that shows the state estimated error been affected by the faults as shown below. The tracking performance of the desired error accuracy appears to be approximately zero, which successfully demonstrates the analysis of the anticipated accurate signal.
Fig. 16. Estimate error of $q$-axis rotor system

V. CONCLUSIONS

This paper has presented the results of fault detection and diagnosis for wind turbine. An augmented observer-based technique has been applied to estimate fault diagnosis which has proved to be able to detect, diagnosed and estimate all faults as well as state system error of the wind turbine dynamics system. FDD has been made to be sensitive to all possible faults in wind turbine system, of which the real data simulation has proven the approach as effective. The proficiency of the proposed methods is appropriate for demonstrating the system efficiency. However, the performance and the response of these selected parameters are excellent in estimating faults in the system.

ACKNOWLEDGMENT

I would like to appreciate my family for their financial support towards my research as well as my able, strong supervisory team for always being there for me.

REFERENCES