Active Fault Tolerance Control For Sensor Fault Problem in Wind Turbine Using SMO with LMI Approach

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Abstract*— *In this paper, we start to investigate the sensor fault problem in a Wind Turbine model with Fault Tolerant Control (FTC). FTC is used to allow the parameters of the controller to be reconfigured in accordance error information obtained online from sensors to improve the stability and overall performance of the system when an error occurs. The design is divided into two parts. The first part is designed Sliding Mode Observer (SMO) based Fault Detection Filter (FDF) to generate a residual signal to estimate fault. FDF is designed to maximize sensitivity fault. The second is a design output feedback control and Fault Compensation to guarantee the stability and performance system from disturbance by ignoring faults.

Moreover, the function of fault compensation is to minimize effect fault of the system. The main contribution of this research is FTC proved to solve the sensor fault problem in a Wind Turbine model. The simulation showed the effectiveness of this method to estimate the fault and stabilized the system faster to a steady condition.

Keywords*— *Fault Tolerant; Sliding Mode Observer; Linear Matrix Inequality; Wind Turbine

I. Introduction

Utilization of renewable energy sources is also a suitable solution as a replacement for conventional energy sources that are depleting the number of reserves. Wind energy is one example of an energy source that has shown an increase in the contribution to electricity demand, using renewable energy sources, the use of wind energy, causing decreasing in use of carbon energy [1].

In long-term operation, wind turbine disturbances are considered for various sensors and actuators. To resolve the system errors, a method to compensate for the errors in the system so that the system can have good performance is required. This method is called Fault Tolerant Control (FTC). There are two types of methods in the FTC, namely Passive Fault Tolerant Control Schemes (PFTCs) and Active Fault Tolerant Control Schemes (AFTCS). In PFTCs, the controller parameters are fixed and designed using robust controls to ensure the control system remains capable of resolving errors from system components. In the PFTCs method, no online error information is required for the controller but has an error limit to overcome. While the AFTCS method, the parameters of the controller are reconfigured according to the error information obtained online to improve the stability and overall performance of the system when an error occurs on the component [2].

The sensor fault case can be classified under sensor saturation, lost sensitivity, and missing measurement. The AFTC scheme for of the actuator or sensor measurement results is based on the error compensation reconstructed with the injection signal. For the sensor fault case such as sensor saturation and lost sensitivity, the AFTC using robust H_∞ method has been developed in [3]. In fault estimation result from that research, the fault cannot accurately estimate using Luenberger observer with LMI approach. According [4], comparing with another scheme, the sliding mode observer base estimation of fault can make the error estimation can convergence to zero even though the signal fault is time-variant.

In this paper, we design the active fault tolerant control with the sliding mode observer to estimate the fault in the sensor of the wind turbine. Then, output feedback controller based on model reference is designed to control the power of the generator although the wind speed is changing. The fault reconstruction is designed with the LMI approach to reject the fault after its estimated.

II. The Mathematical Model of Wind Turbine

A. Wind Model

The main driving force for the wind turbine is a Wind with depends on multiple parameters. Generally, wind model described into two-part, The mean wind model and the stochastic model [5].

In [6], there is three variable that influences the stochastic model of wind. Wind shear which is the effect of wind energy lost at the surface of the earth, tower shadow is the phenomenon when a blade located in front of the tower, the lift on that blade decreases because the tower reduces the effective wind speed. This tower shadow implies that force acting on each blade decreases every time a blade is in front of the tower. An equation describing the wind component is described bellow

$$v_w(t) = \bar{v}_w(t) + v_{ws}(t) + v_{ts}(t) + v_s(s) \quad (1)$$

In Eq. (1) $\overline{v}_w$ is the mean wind speed that is occurring in certain intervals; v_{iews} and v_{ts} is the wind shear and tower shade that effect in the wind force in the blade; and v_s. is the stochastic effect in the wind which completely described in [6].

B. Aerodynamic Model

The aerodynamics model of the wind turbine model is modeled as torque acting in a blade which described below [5]

$$T_a(t) = \frac{1}{2\omega_r}\varrho A v_r^3(t) C_p(\lambda(t),\beta(t)) \tag{2}$$

Where ϱ air density, A is the swept rotor area, v_r is the wind speed passing through the rotor, and $C_p(\lambda(t),\beta(t))$ is a mapping of the torque coefficients. The C_p coefficient modeled as the lookup table depending on the tip speed ratio and the pitch angle.

C. Drive Train

The purpose of the drive train is to transfer torque from the rotor to the generator. It includes a gearbox that increases the rotational speed from the low-speed rotor side to the high-speed generator side. In this paper, the drive train is modeled by a two-mass model.

$$J_r\dot{\omega}_r(t) = T_a(t) - K_{dt}\theta_\Delta + (B_{dt} + B_r)\omega_r(t) + \frac{B_{dt}}{N_g}\omega_g(t) \tag{3}$$

$$J_g\dot{\omega}_g = \frac{\eta_{dt}K_{dt}}{N_g}\theta_\Delta(t) + \frac{\eta_{dt}B_{dt}}{N_g}\omega_r(t) - \left(\frac{\eta_{dt}B_{dt}}{N_g^2} + Bg\right)\omega_g - T_a(t) \tag{4}$$

$$\dot{\theta}_\Delta(t) = \omega_r(t) - \frac{1}{N_g}\omega_g(t) \tag{5}$$

Where J_r is the moment of inertia of the low-speed shaft? K_{dt} is the torsion stiffness of the drive train, B_{dt} is the torsion damping coefficient of the drive train, Bg is the viscous friction of the high-speed shaft, N_g is the gear ratio, J_g is the moment of inertia of the high-speed shaft, η_{dt} is the efficiency of the drive train, and θ_Δ is the torsion angle of the drive train.

D. Generator Model

The electrical system in the wind turbine and the electrical

System controllers are much faster than the frequency range used in the wind model. On a system level of the wind turbine, the generator and converter dynamics can be modeled by a first-order transfer function

$$\dot{T}_g(t) = -\frac{1}{\tau_g}T_g(t) + \frac{1}{\tau_g}T_{g,ref}(t) \tag{6}$$

where $T_g(t)$ is the torque in generator and $T_{g,\,ref}(t)$ torque reference in generator and τ_g is the time constant parameter on the generator.

The power supplied by generator described as below

$$P_g = \eta_g\omega_g(t)T_g(t) \tag{7}$$

Where η_g is the efficiency of the generator.

E. Pitch Actuator

Pitch actuator system is the hydraulic system that controls the pitch angle in the blade of the wind turbine. The controller is not available. In principle, it is a piston servo system that can be modeled well by a second-order transfer function between the measured angle β and pitch reference β_{ref} [1]

$$\frac{\beta}{\beta_{ref}} = \frac{1}{s^2 + 2\zeta\omega_n + \omega_n^2} \tag{8}$$

where ζ is the damping ratio, and ω_n is the natural frequency of the pitch actuator.

F. Linearization

The system has two inputs, the generator torque reference and the pitch angle reference, which are delayed as prior explained. Furthermore, the speed of the wind acts as a disturbance and is an uncontrolled input. The aerodynamic model is a▪ ected by the e▪ ective wind speed, $v_r(t)$ a▪ ecting the real wind speed, $v_w(t)$. If the chosen state variable is $[T_g \quad \dot{\beta} \quad \beta \quad \theta_\Delta \quad \omega_g \quad \omega_r]^T$ the state space model of the wind turbine is described as following equation

$$\dot{x}(t) = Ax(t) + Bu(t) + Bdv_w(t) \tag{9}$$

Where

$$A = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & a_{32} & a_{33} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & a_{45} & 1 \\ a_{51} & 0 & 0 & a_{54} & a_{55} & a_{56} \\ 0 & a_{62} & 0 & a_{64} & a_{65} & a_{66} \end{bmatrix}; B = \begin{bmatrix} b_{11} & 0 \\ 0 & 0 \\ 0 & b_{23} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$Bd = [0 \quad 0 \quad 0 \quad 0 \quad 0 \quad bd_6]^T$$

And the parameter is described bellow

$$a_{11} = -\left(\frac{1}{Tg}\right) \qquad a_{66} = -\left(\frac{Bdt + Br}{Jr} + \frac{1\,\vartheta Ta}{Jr\vartheta\omega r}\right)$$

$$a_{33} = -2\zeta\omega_n \qquad a_{32} = -\omega_n^2$$

$$a_{45} = -\left(\frac{1}{Ng}\right) \qquad b_{11} = \frac{1}{Tg}$$

$$a_{51} = -\left(\frac{1}{Jg}\right) \qquad b_{32} = -\omega_n^2$$

$$a_{62} = \frac{1\,\vartheta Ta}{Jr\,\vartheta\beta} \qquad bd_6 = \frac{1\,\vartheta Ta}{Jr\vartheta Vr}$$

$$a_{64} = \frac{Kdt}{Jr} \qquad a_{52} = \left(\frac{Ndt\quad Kdt}{Jg\,Ng}\right)$$

$$a_{55} = \frac{Bdt}{BgJr} \qquad a_{53} = -\left(\frac{Ndt + Bdt}{JgNg2} + \frac{Bg}{Jg}\right)$$

$$a\_54 = -\left(\frac{Ndt}{NgJg}\right)$$

In eq (9) there is the nonlinearly term in aerodynamic model of wind turbine. In linearization of wind model, the nonlinearly term of $\frac{\vartheta Ta}{\vartheta\beta}, \frac{\vartheta Ta}{\vartheta Vr}, \frac{\vartheta Ta}{\vartheta\omega r}$ directly approximately using parameter identification [5].

III. Fault Detection with SMO

Consider the linear system with the sensor fault is described in the following equation

$$\dot{x}(t) = Ax(t) + Bu(t)$$
$$y(t) = Cx(t) + D_f f(t) \quad (10)$$

where $y(t)$ is the output of system and $f(t)$ is the fault that occurs in the sensor of the output state.

In this section, SMO is designed to estimate the faulty in the system. Since (A, C) is detectable, given SMO the following in equation

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + L(y(t) - \hat{y}(t)) + Gv(t)$$
$$\hat{y} = C\hat{x}(t) \quad (11)$$

Where $\hat{x}(t) \in R^n$ and $\hat{y}(t) \in R^n$ represent state and output estimation vector. (Vt) is switching term of SMO signal. Observer gain L and G should be guaranteed the stability of the observer. If Filtering error estimation is given in equation (12) and the derivation in (13)

$$e = x(t) - \hat{x}(t) \quad (12)$$

$$\dot{e} = \dot{x}(t) - \dot{\hat{x}}(t) \quad (13)$$

substitute (10) and (11) into (13) so we have the error dynamics of the observer in equation

$$\dot{e} = (A - LC)e(x) - L(D_f f(t)) + Gv(t) \quad (14)$$

If given the Lyapunov function in equation

$$\dot{V} = \dot{e}^T Pe + e^T P\dot{e} + e^T e - \gamma f^T f \quad (15)$$

Substitute (14) into (15) we obtain LMI in equation

$$\begin{bmatrix} Q & PLD_f \\ * & \gamma I \end{bmatrix} < 0 \quad (16)$$

Where $Q = A^T P + PA - PLC - C^T L^T P$ and $P^T = P \geq 0$ is the solution of Q, then the error estimation is asymptotically stable. When the error estimation is convergence to zero the fault estimation given in equation

$$\hat{f}(t) = (y - \hat{y}) \quad (17)$$

IV. Output Feedback Control and Fault Reconstruction

In this section, the output feedback control will be design with the model following form. The second order model following form is described in the following equation

$$\begin{bmatrix} \dot{x}_m \\ \dot{x}_{m+1} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -(a*b) & -(a+b) \end{bmatrix}\begin{bmatrix} x_m \\ x_{m+1} \end{bmatrix} + \begin{bmatrix} 0 \\ (a*b) \end{bmatrix} r \quad (18)$$
$$y_r = Cx_m$$

where a and b are the poles which must be chosen to desire characteristic of the closed-loop system.

If the error system was chosen is between output model reference and output state

$$e_s = y_r - y \quad (19)$$

also, the control signal is below

$$u = K * e + V\hat{f} \quad (20)$$

So, we have the system dynamic become

$$\dot{x} = (A + BVC)x - (BKC + BVC)\hat{x} + BKCx_r + BVD_f f \quad (21)$$

also, the observer

$$\dot{\hat{x}} = (LC + BVC)x + (A - LC - BKC - BVC)\hat{x} + BKC_r x_r + (LD_f + BVD_f)f \quad (22)$$

If we join the eq.(18),(21) and eq.(22) so we have the augmented dynamic system in equation

$$\dot{\bar{z}} = A_i \bar{z} + B_i \bar{w} \quad (23)$$

Where $\bar{z} = [x \quad x_r \quad \hat{x}]^T$, $\bar{w} = [r \quad f]$ and

$$A_i = \begin{bmatrix} (A + BVC) & BKC_r & -(BKC + BVC) \\ 0 & A_r & 0 \\ (LC + BVC) & BKC_r & (A - LC - BKC - BVC) \end{bmatrix};$$

$$B_i = \begin{bmatrix} 0 & BVD_f \\ B_r & 0 \\ 0 & (LD_f + BVD_f) \end{bmatrix}$$

Consider the Lyapunov function described in the equation below

$$\dot{V} = \dot{\bar{z}}^T \bar{Y}\bar{z} + \bar{z}^T \bar{Y}\dot{\bar{z}} + \bar{z}^T \bar{R}\bar{z} - \rho \bar{w}^T \bar{w} \quad (24)$$

So, we have the LMI in the following equation

$$\begin{bmatrix} (A_i^T \bar{Y} + \bar{Y}A_i) + \bar{R} & \bar{Y}B_i \\ B_i^T \bar{Y} & -\gamma \end{bmatrix} < 0 \quad (25)$$

where

$$\bar{Y} = \begin{bmatrix} Y & 0 & 0 \\ 0 & Y & 0 \\ 0 & 0 & Y \end{bmatrix}; \bar{R} = \begin{bmatrix} R & 0 & 0 \\ 0 & R & 0 \\ 0 & 0 & R \end{bmatrix};$$

$Y = Y^T \geq 0$ and $R = R^T \geq 0$ is the solution of error system convergence to zero.

V. Simulation Result

A. Without Faulty Case

The first step we tested the output feedback controller. In this simulation, the desired power of the generator is $4x10^6$ Watt with eq.(7) we calculate $\omega_g(t)$ and $T_g(t)$ to the model following reference.

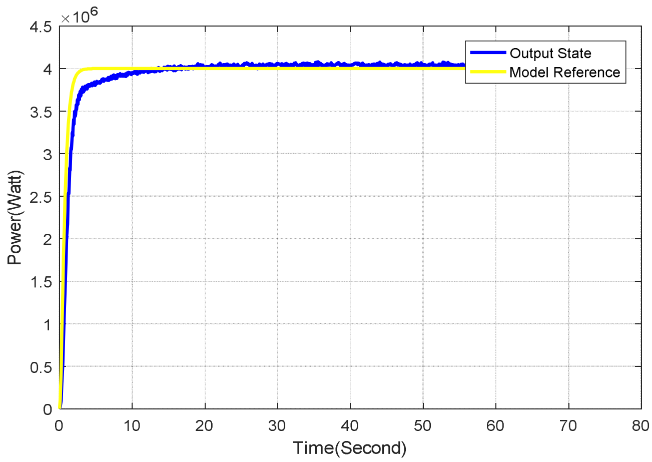

Fig. 1 Generator output power without a faulty case with output feedback controller.

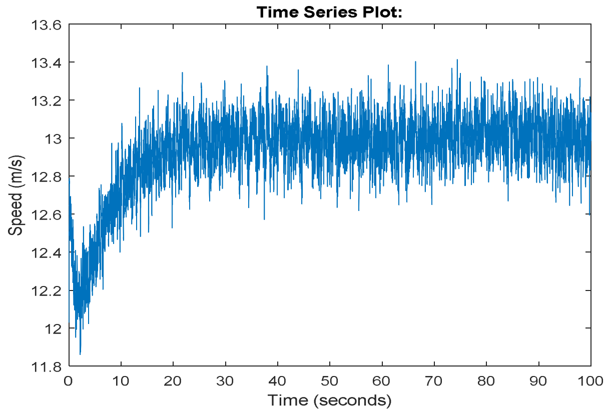

Fig. 2 wind speed

From the simulation, we get that the output feedback control can follow the model reference in 10 seconds with the root mean square error of around 0.132.

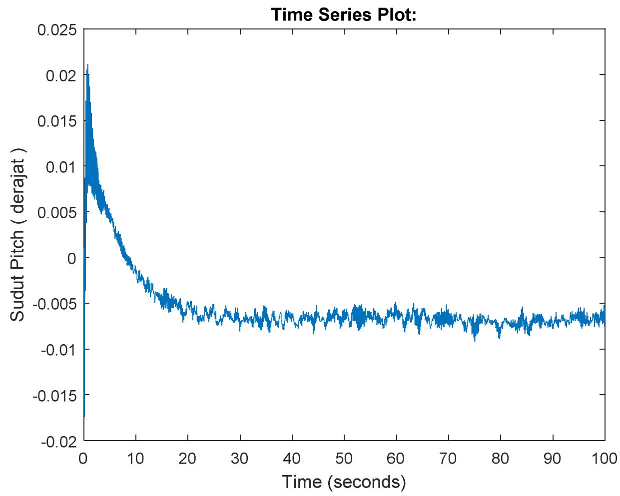

Fig. 3 The angle of pitch signal

FFig. 2 and Fig. 3, its show that the output feedback control with the LMI approach can stabilize the power generator although the wind speed is changing. The robustness from the formulation in LMI shows that the wind speed becomes disturbance successfully handled.

B. Faulty Case in One Sensor

In a faulty sensor case, the fault is injected in the second output of the system, i.e., $\omega_g(t)$. From the simulation, it can be shown that the SMO can accurately estimate the fault, its shown from Fig. 4.

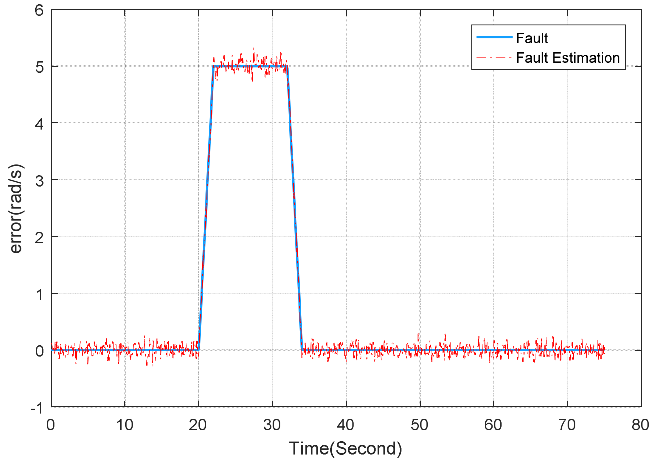

Fig. 4 Comparison of fault and fault estimation using SMO

Fig. 5 shows that the controller responds by comparing when using fault tolerant control and without using fault tolerant control when an error occurs. From the response obtained at that time without fault tolerant control, the output state of the plant had increased and not on the set point due to the giving of the error and just returned to the set points when no error occurred. Meanwhile, when using fault tolerant control when given interference, the response will return to the set points faster 3 seconds when compared with no interference, the response is faster because of the reconfiguration of the control of the addition of set point when the occurrence of errors.

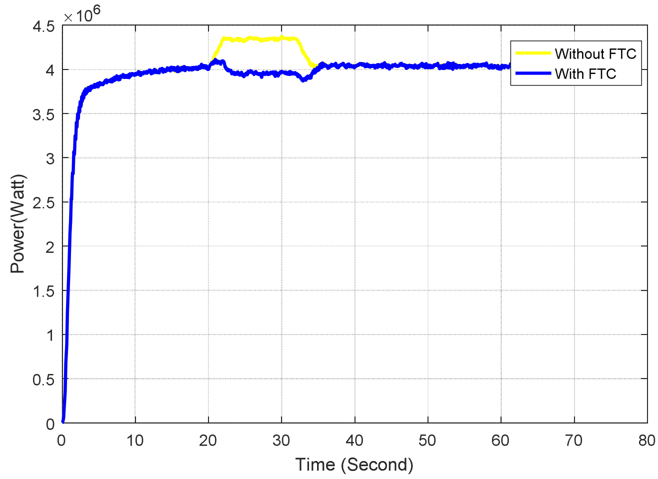

Fig. 5 Comparison with and without FTC

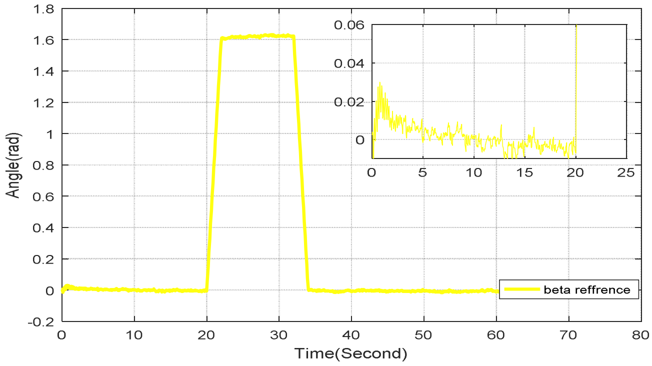

Fig. 6 Angle of pitch signal

VI. CONCLUSION

After doing the system modeling then do the testing and analysis, it can be taken some conclusions as follows; Design of sliding observer mode used can estimate the fault case at the plant that happened faultily.

Active fault tolerance method is used to overcome the interference and maintain the stability of the system running under the desired output when the interference can be re-stable as when there is no error. Active fault tolerance works successfully in the first second during the interruption.

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