Fault Tolerant Control Using L0 Norm Constraint Optimization in MATLAB for Estimating Sensor and Actuator Fault in Wind Turbine

Putri Yeni Aisyah[1*], Katherin Indriawati[2]

***Abstract*— The availability of onshore wind power plant systems (PLTB) reaches 98%, but the maintenance costs required are still very high for the wind turbine system. Meanwhile, the availability of offshore PLTB is decreased by 60% due to the main cause of damage to some components in wind turbine systems. This study proposes the use of fault estimation methods of sensor and actuator in fault tolerant control (FTC) strategy, especially in Wind Turbine. The fault estimation method is build using the ℓ_0 norm constraint optimization. The optimization formulation with ℓ_0 norm constraint is derived by applying the compressed sensing technique so that the estimation of the bias error can be used to estimate the fault of several components by a single observer. This answers the observability issues encountered in single observer use cases. The proposed implementation of observers with the FTC results in better response characteristics when compared to systems without FTC. Response characteristics on actuator fault of 0.3 – 1.3pu, system with observers resulting in a maximum undershoot value of 0.4-1% while systems without observers resulting in a maximum undershoot value of 6.2-26.4%. The characteristics of the response with the observer on sensor fault resulting 0.3-1.3pu resulting in value of 1.6-4%, 0% and 63.9- 70.7s. System without observers, with sensor fault of 0.3-1.3pu resulting in maximum undershoot, steady state error and settling time of 6.2-26.2%, 6.2-26.4%, and 0s**

***Keywords*— Bias fault estimation, Compressed sensing, Fault tolerant control, Wind turbine generator**

I. INTRODUCTION

Nowadays, wind energy is becoming much noticed. It is because wind energy has several advantages including unlimited energy production so that it can be used as an alternative measure of fossil energy savings as an energy source [1]. Low wind speed range causes turbine controllers to work by optimizing power extraction through controlling wind turbine rotor speed following optimal rotor speed. Thus, power optimization efforts need a control system for optimal rotor speed tracking [2]. Tracking accuracy provides a greater chance of component faults in wind turbine generator systems, especially in wind turbine drive train parts that gain extra load on their shafts. Thus, the control systems involved in wind turbine systems should be able to tolerate the impact of emerging faults. Control strategies that tolerating the impact of emerging faults are known as fault-tolerant control (FTC) strategies and a growing new field of research in the field of control science [3]. FTC systems are designed to accommodate errors so that minor errors in components do not cause system failures. FTC strategy consists of two types, passive and active FTC [4]. One of the methods in active FTC (AFTC) is error compensation by using error estimation results.

The common error estimation method is at the fault detection and identification (FDI) stage in the FTC scheme by using an observer [5].

At first, each error variable is estimated with an observer, so the resulting structure becomes complex for the case of multiple error variables, as there are several observers built in. Thus, the use of a single observer was developed to estimate several error variables. However, the use of a single observer requires a measurement variable whose number must be equal to the number of error variables [6].

Several research developments on the FTC scheme for WTG and error estimation, including previous research by Patton and Klinkhieo [7] is about using an augmented state observer-based disturbance observer to estimate the actuator error. However, this method requires observation of the error variable. The next observation problem is solved by [8]. The method used is based on compress sensing. The error being reviewed is a bias error that occurs at one time (not simultaneously). Estimated error bias is formulated as an optimization problem with ℓ_0 norm constraint.

Therefore, this study proposes the use of the error estimation method of the WTG system components using the FTC strategy. This estimation method has a simple structure because it uses only a single observer ℓ_0 *norm constraint*. This estimation method has a simple structure because it uses only a single observer. Optimization formulation with ℓ_0 norm constraint is derived by applying compressed sensing technique. So that bias error estimation can be used to estimate all actuator components and sensors by a single observer. Optimization with ℓ_0 norm constraint answers observability problems. The estimation results are used for compensating sensor and actuator errors in FTC scheme.

[1]Departmet of Instrumentation Engineering, Faculty of Vocational Studies, Institut Teknologi Sepuluh Nopember, Kampus ITS Sukolilo, Surabaya 60111, Indonesia, Email: putri.yeni@its.ac.id

[2]Department of Engineering Physics, Faculty of Industrial Technology and System Engineering, Institut Teknologi Sepuluh Nopember, Kampus ITS Sukolilo, Surabaya 60111, Indonesia, Email: kindriawati@ep.its.ac.id

II. METHOD

A. System Modeling and Wind Turbine Specification

The wind turbine system model used is in per unit (pu). System (pu) is a way of simplifying a calculation value that is useful in the analysis of electric power systems. In the system (pu), the actual value can be referred back to its reference value. The state space equation is obtained from the wind turbine dynamic model, which is formulated from the following equations.

$$\dot{\theta}_\Delta = \omega_r - \omega_g \tag{1}$$

Furthermore, the rotor mechanical torque can be modeled as:

$$T_m = \theta_\Delta K_{sh} + (\omega_r - \omega_g) D_{mutual} \tag{2}$$

Equation (2) is substituted to equation (1) to get the following equation

$$\dot{\omega}_r = \frac{T_a}{2H_{wt}} - \frac{(\omega_r - \omega_g) D_{mutual}}{2H_{wt}} - \frac{\theta_\Delta K_{sh}}{2H_{wt}} \tag{3}$$

The next stage is modeling the generator. The generator modelling in pu units can be written in equation (4).

$$\dot{\omega}_g = \frac{\theta_\Delta K_{sh} - (\omega_r - \omega_g) D_{mutual} - T_g - F\omega_g}{2H} \tag{4}$$

The generator is modeled only as a mechanical model, which can be simplified with the first order system. The model is written in equation (5)

$$\dot{T}_g = -\frac{1}{\tau_g} T_g + \frac{1}{\tau_g} T_{g,ref} \tag{5}$$

thus, $T_{g,ref}$ and τ_g is the torque generator reference and the constant time

Wind torque T_a which is unknown in value and cannot be measured, can be considered a nuisance on this model. So that it is treated as an error that affects the state equation, so the wind turbine state space equation becomes linear.

There are two measurable variables in this control system: T_g and ω_g. Speed sensor error is a bias of β (pu). Where β is the sensor error gain on the tachometer so that the wrong measurement used is $\omega_g + \beta$ (pu). The input voltage of the converter is controlled by a DC-DC converter. So that the actuator error can be simulated as a loss of effectiveness of the converter.

The dynamics of the converter to calculate the generator torque can be approached with a first order system with a delay time. Expressed in the following transfer function equation:

$$t_g \frac{T_g(s)}{T_{g,ref}(s)} = \frac{1}{t_g s + 1} \tag{6}$$

Sensor error provides incorrect information for the nominal control algorithm. The output value fed to nominal control due to sensor error is written in the equation below.

$$\omega_c = \omega_m - F_s \hat{f}_s \tag{7}$$

F_s determined from the plant state space equation model. It is assumed that the sensor error only occurs on the generator speed sensor so that the sensor error distribution matrix becomes:

Speed sensor modeled as first order system with specific time constants ($\boldsymbol{\tau}$). Transfer function for speed sensor is written in equation (6)

$$\omega_g \frac{\omega_g(s)}{\omega_{g,nom}(s)} = \frac{1}{\tau_g(s)+1} \tag{8}$$

Thus, the state space equation that accommodates actuator errors and changes in wind torque is written in the following equations:

$$\dot{x}(t) = Ax(t) + Bu(t) + D_d d(t) \tag{9a}$$

$$y(t) = Cx(t) + D_n n(t) + F_s f_S(t) \tag{9b}$$

with, $x(t)$, $y(t)$, $u(t)$, $d(t)$, $n(t)$, $f_S(t)$ is vector *state*, input, output, unknown interference (including actuator errors), noise measurements, and sensor errors.

$$\begin{bmatrix} \dot{T}_g \\ \dot{\omega}_r \\ \dot{\omega}_g \\ \dot{\theta}_\Delta \end{bmatrix} = \begin{bmatrix} -\frac{1}{\tau_g} & 0 & 0 & 0 \\ 0 & -\frac{D_m}{2H_{wt}} & \frac{D_m}{2H_{wt}} & -\frac{K_{sh}}{2H_{wt}} \\ -\frac{1}{2H} & \frac{D_m}{n_g.2H} & -\frac{(D_m+F)}{n_g^2.2H} & \frac{K_{sh}}{n_g^2.2H} \\ 0 & 1 & -\frac{1}{n_g} & 0 \end{bmatrix} \begin{bmatrix} T_g \\ \omega_r \\ \omega_g \\ \theta_\Delta \end{bmatrix} + \begin{bmatrix} \frac{1}{\tau_g} \\ 0 \\ 0 \\ 0 \end{bmatrix} T_{g,ref} + \begin{bmatrix} \frac{1}{\tau_g} & 0 \\ 0 & \frac{1}{J_r} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} f_a \\ T_a \end{bmatrix} \tag{10}$$

Based on the explanation above, there are only two errors that need to be estimated, speed sensor errors and converter actuator errors. So, the output matrix and error distribution matrix for observer design are defined as:

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix},$$

$$F_s = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$F_a = \begin{bmatrix} \frac{1}{\tau_g} & 0 \\ 0 & \frac{1}{H_{2wt}} \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Meanwhile, the desired output according to the setpoint is the speed so the distribution matrix is defined as:

$$C1 = \begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix}$$

B. Designing a State Feedback Controller

The control system is a process of maintaining a controlled variable at a certain value so that the system is stable. One of the control system schemes used in industry is shown in Figure 1.

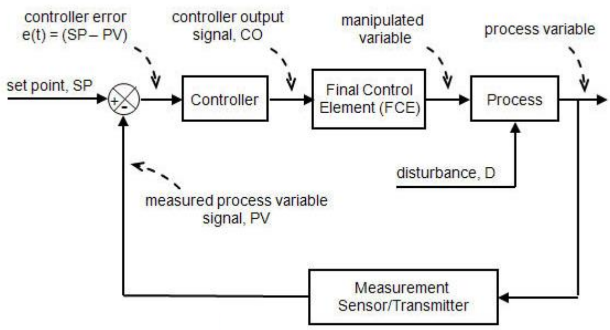

Figure 1. Closed control system block diagram [9]

The first step in designing the FTC is designing nominal controls. At the design stage of the state feedback control system using this following state space equation,

$$\dot{x} = Ax + Bu \tag{11}$$

$$y = Cx + Du \tag{12}$$

thus, $x = \begin{bmatrix} T_g \\ \omega_g \end{bmatrix}$ is torque generator (T_g) and generator speed (ω_g). Meanwhile the desired output following the setpoint is the speed of the generator, so that:

$$y_r = C_r \, . x \;=\; [0 \quad 1] \begin{bmatrix} T_g \\ \omega_g \end{bmatrix} = \omega_g \tag{13}$$

C. Observer Algorithm Design and Fault Estimation with Optimization L0 Norm Constraint

The discrete system is used to describe the observer method that will be designed because the method used based on Kalman Discrete time filter with the representation of the following state space equation

$$x(k+1) = A_d x(k) + B_d fa(k) + B_d \bar{u}(k) \tag{14a}$$
$$\bar{y}(k) = C_d x(k) + f_s(k) \tag{14b}$$

Augmentation system with state bias from sensor errors and actuators is written in equation below

$$\begin{bmatrix} x(k+1) \\ fa(k+1) \\ fs(k+1) \end{bmatrix} = \begin{bmatrix} A_d & B_m & O \\ O & I_m & O \\ O & O & I_m \end{bmatrix} \begin{bmatrix} x(k) \\ fa(k) \\ f_s(k) \end{bmatrix} + \begin{bmatrix} B_d \\ O \\ O \end{bmatrix} \bar{u}(k) \tag{15a}$$

$$\bar{y}(k) = [C_d | \, O \; I_m] \begin{bmatrix} x(k) \\ fa(k) \\ f_s(k) \end{bmatrix} \tag{15b}$$

As mentioned in the introduction, to solve the problem of observability, error estimation can be done with a single observer based on the optimization of the ℓ_0 norm constraint.

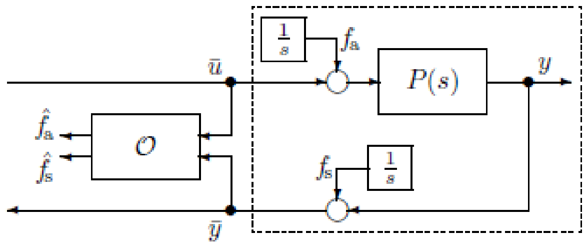

Figure 2. Estimated bias fault by the observer [8]

ℓ_0 norm is the number of non-zero components in a system that is widely used to determine the hidden model of measured data. Optimization of ℓ_0 norm by finding the minimum value can be used to search for hidden models. ℓ_0 norm optimization is also called compressed sensing (CS).

$$\|f\|_0 = 1 \tag{16}$$

where

$$f := [f_a^T \; f_s^T]^T \tag{17}$$

`Kalman Filter is an algorithm or collection of mathematical equations that produce an efficient calculation to estimate the state of the process with the aim of minimizing noise or variance against other references.

Estimation of the bias error of the augmentation system with $\ell 0$ norm can be formulated as:

minimize $\|\bar{y} - [P(1) \; I_m] f\|_2$ subject to $\|f\|_0 = 1$ (18)

minimize $\|f\|_0$ subject to, $\bar{y} = [P(1) \; I_m] f$ (19)

However, optimization of ℓ_0 norm is a very complicated optimization problem. Therefore, with the Basic Pursuit method, the optimization problem with ℓ_0 norm can be replaced by reconstructing the combination from ℓ_1 norm.

minimize$\|f\|_1$ subject to $\bar{y} = [P(1) \; I_m] f$ (20)

This method is applied to the Kalman Filter using *pseudo measurement*.

Pseudo measurement in Kalman filter minor loop is ℓ_1 norm of the estimated state and Pseudo measurement is set to 0

$$0 = \|\tilde{\hat{x}}\|_1 = [sign(\tilde{\hat{x}}) \ldots sign(\tilde{\hat{x}}_{n+2m})] \tilde{\hat{x}} \tag{21}$$

Based on the explanation of Kalman filter stages and compressed sensing, the equation used as a reference 'Algoritma Compressed Sensing Embedded Filter Kalman' in this study is described by equations (22) to (27).

Prediction Stage:

$$\tilde{\hat{x}}_{k+1|k} = \tilde{A} \tilde{\hat{x}}_{k|k} + \tilde{B} \bar{u}_k \tag{22}$$
$$P_{k+1|k} = \tilde{A} P_{k|k} \tilde{A}^T + Q \tag{23}$$

Measurement Update Stage

$$K_k = P_{k+1|k} \tilde{C}^T (\tilde{C} P_{k+1|k} \tilde{C}^T + R)^{-1} \tag{24}$$
$$\tilde{\hat{x}}_{k+1|k+1} = \tilde{\hat{x}}_{k+1|k} + K_k (\bar{y}_k - \tilde{C} \tilde{\hat{x}}_{k+1|k}) \tag{25}$$
$$P_{k+1|k+1} = (I - K_k \tilde{C}) P_{k+1|k} \tag{26}$$

Compressed Sensing embedded Kalman Filter Stage

Let $P^1 = P_{k+1|k+1}$ and $\tilde{\hat{x}}^1 = \tilde{\hat{x}}_{k+1|k+1}$

For $\tau = 1, 2, \ldots, N_\tau - 1$ iterations

$$H_\tau = \begin{bmatrix} O_{1xn,} \; \omega_{n+1} sign(\hat{f}_{a_1}^\tau) \ldots \omega_{n+m} sign(\hat{f}_{a_m}^\tau), \\ \omega_{n+m+1} sign(\hat{f}_{s_1}^\tau) \ldots \omega_{n+2m} sign(\hat{f}_{sm}^\tau) \end{bmatrix} \tag{27a}$$

$$K^\tau = P^\tau H_\tau^T (H_\tau P^\tau H_\tau^T + R_\epsilon)^{-1} \tag{27b}$$
$$\tilde{\hat{x}}^{\tau+1} = (I - K^\tau H_\tau) \tilde{\hat{x}}^\tau \tag{27c}$$
$$P^\tau = (I - K^\tau H_\tau) P^\tau \tag{27d}$$
$$P^{\tau+1} = P^\tau + Q_\epsilon$$

End for

set $P_{k+1|k+1} = P^N$ and $\tilde{\hat{x}}_{k+1|k+1} = \tilde{\hat{x}}^{N_\tau}$ (27e)

D. FTC System Design

In this study, the FTC system is designed in the form of a simulated wind turbine speed control system. While the simulated error occurs in the sensor f_s and actuators f_a. After the observer simulation is performed, the next step is to reconfigure the control signal. The reconfiguration technique that is carried out is the compensation technique.

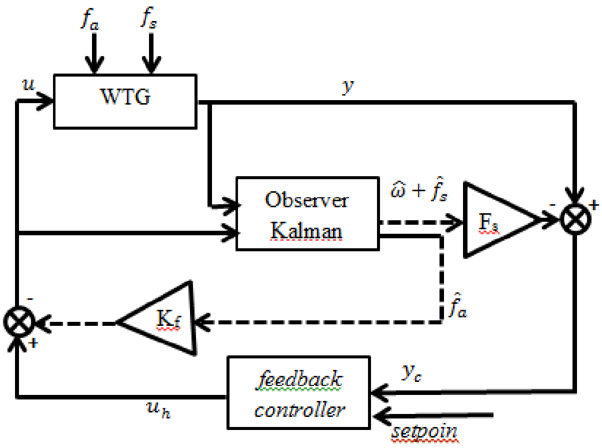

Figure 3. FTC scheme

E. Bias Fault Testing

The FTC strategy carried out in this study uses a compensation technique. In a control system, actuator errors have a direct impact on changes in global control inputs applied to the system. Meanwhile, the sensor error provides wrong information for the control algorithm, so it provides wrong information for the control algorithm to be incompatible with the required.

The most common actuator error compensation strategies used in an FTC system can be stated as the following equations:

$$u = u_h + u_c \quad (27)$$

$$u = u_k - K_f \hat{f}_a \quad (28)$$

where u_h is the nominal (torque) control input and u_c is the additive control input to compensate for the impact of the error. Sensor error compensation is to prevent misinformation for the nominal control algorithm. The output values fed to the nominal controller are:

$$\omega_c = \omega_m - F_s \hat{f}_s \quad (29)$$

III. Results and Discussions

A. Controller Tracking Test Results

Before carrying out the observer test, it is necessary to design and test the controller first. This is to ensure that the designed controller is able to track the setpoint value with the controller gain value obtained. In the tracking test, given a change of set points from 5m/s to 10 m/s at the 100th second. The state feedback control system response graph is shown in Figure 4.

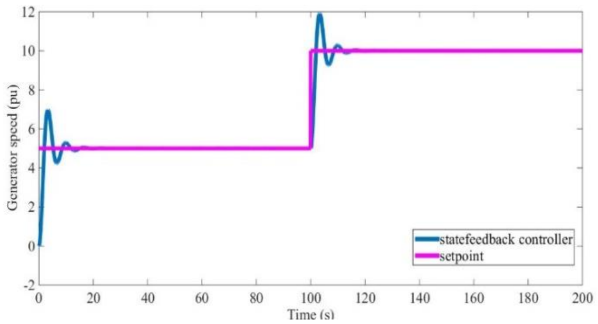

Figure 4. State feedback controller system design response

In Figure 4, the purple line shows the setpoint value and the blue graph shows the result of the state feedback controller. From the graph can be known that the designed state feedback controller system can work well because it is able to reach the setpoint value. From the response, the value of the controller criteria is maximum undershoot / overshoot and error steady state of 0%, while the settling time value is 11.2 seconds.

B. Observer Estimation Test Results

Observer test results need to be conducted to determine observer's ability in estimating wind turbine speed as a controlled variable in this study. The simulation is carried out by comparing the response of system simulation results with and without observers.

In this study, the covariance matrix used for the Kalman Filter observer is

$$Q = \begin{bmatrix} 8 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 8 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 8 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 8 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 6 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 6 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 6 \end{bmatrix} X\, 10^{-2}$$

$$R = [8 \quad 0] x 10^{-2}$$

$$R_e = 9\hat{\ }2x10$$

$$Q_e = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} X 10^{-3}$$

In this study, m= 2. By applying optimization ℓ_0 norm constraint, several parameter values obtained, the value of g and the angle (ϴ) between the orthogonal matrix g. g is the column vector of the orthogonal matrix obtained from equation (3.15). The vector g of the wind turbine generator system used in this study is:

$$g_1 = \begin{bmatrix} 1.0000 \\ -0.0000 \\ -0.0000 \end{bmatrix}$$

$$g_2 = \begin{bmatrix} 0.0000 \\ 0.9999 \\ 0.0096 \end{bmatrix}$$

$$g_3 = \begin{bmatrix} 0.0000 \\ 0.0096 \\ 0.0001 \end{bmatrix}$$

Thus, the angle obtained from the g vector above is:

$$\theta_{12} = 31.3063^0$$

$$\theta_{13} = 99.2166^0$$

$$\theta_{23} = 69.8028^0$$

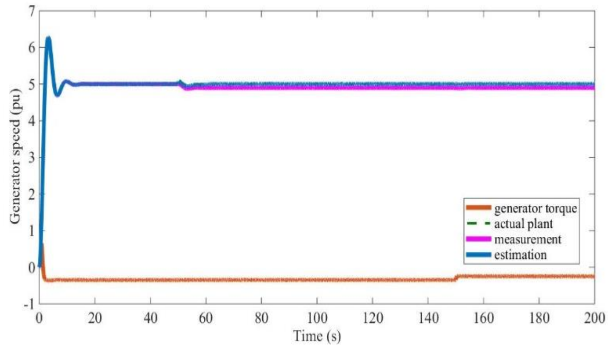

Figure 5. Response to observer estimates

Simulation results without FTC with errors are shown in Figure 5. In the graph, the estimated reading response from the controller without the observer has different results from the plant's actual speed. In Figure 5, the estimated reading by the observer (blue line) shows the same result as the plant's actual speed (green line) and it is able to compensate after the error occurs. This shows that the designed observer is able to estimate if an error occurs.

TABLE 1.
CHARACTERISTIC OF RESPONSE WITHOUT AND WITH OBSERVERS

Parameters	System Design	
	Without FTC	**With FTC**
Maximum Undershoot	10.20%	2.20%
Settling Time	-	63.8s
Error Steady State	0%	0%

The next simulation is done on the plant when an error occurs. The error given in the test is a minor error that is a bias error.

C. Bias Error Test Results on Sensors and Actuators

In this section is given a bias error of 0.1, 0.3, 0.6, and 1.2pu on sensor components and actuator. Bias errors are given at the 50th and 100th seconds.

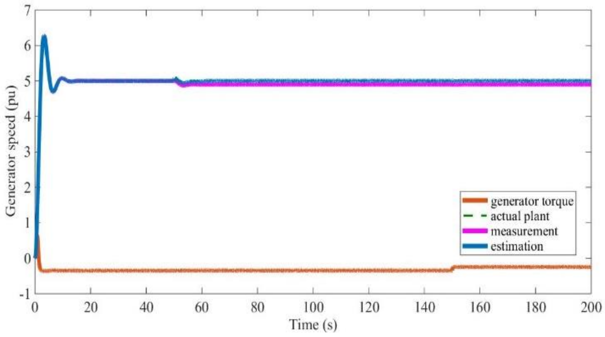

Figure 6. Simulation response with sensor bias fault 0.1 pu

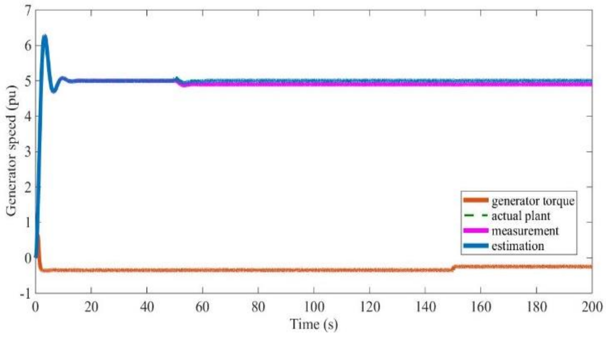

Figure 7. Simulation response with sensor bias fault 0.3 pu

The simulation response obtained will be compared to the response characteristics for each bias error value. In Figure 6 can be seen that the system with FTC given a sensor bias error at the 50th seconds is able to compensate the error so that the response can return to an error-free state (the desired setpoints).

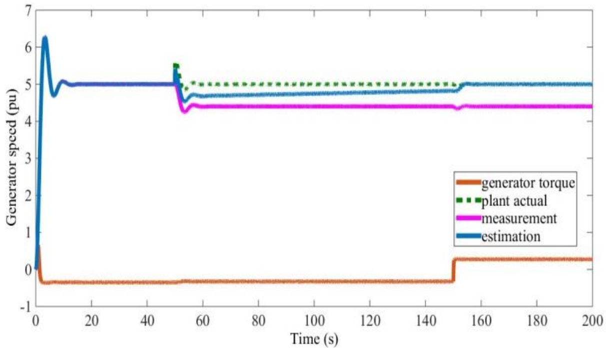

Figure 8. Simulation response with sensor bias error 0.6 pu

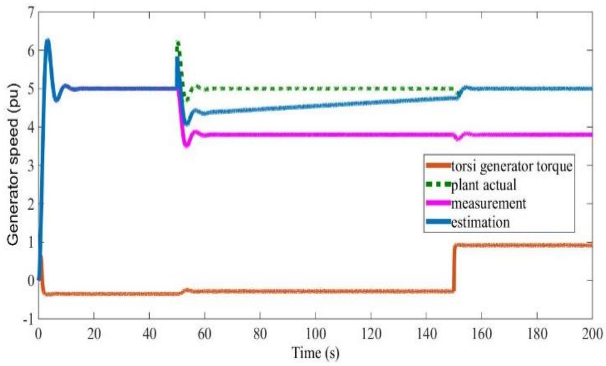

Figure 9. Simulation responsensensor bias fault of 1.2 pu

Response characteristic for bias errors of 0.1-1.2pu on the sensor components are shown in Table 2 and Table 3.

TABLE 2.
OBSERVER RESPONSE CHARACTERISTICS WITHOUT FTC FOR SENSOR COMPONENT

Fault Position	**Sensor Fault**		
	Without FTC		
Error Value	**Max Undershoot**	**Error Steady State**	**Settling Time**
0.1	6.20%	6.20%	0
0.3	10.20%	10.20%	0
0.6	16.20%	16%	0
1.2	26.20%	26.40%	0

TABLE 3.
OBSERVER RESPONSE CHARACTERISTICS WITH FTC FOR SENSOR COMPONENT

Fault Position	**Sensor Fault**		
	With FTC		
Error Value	**Max undershoots**	**Error Steady State**	**Settling Time**
0.1	1.60%	0	63.9s
0.3	2.20%	0	64.1s
0.6	3%	0	70s
1.2	4%	0	70.7s

The response characteristics for error bias in the actuator components are shown in Table 4 and Table 5.

TABLE 4.
OBSERVER RESPONSE CHARACTERISTICS WITHOUT FTC FOR ACTUATOR COMPONENT

Fault Position	**Actuator Fault**		
	Without FTC		
Error Value	**Max undershoots**	**Error Steady State**	**Settling Time**
0.1	0.40%	0	58.6s
0.3	0.58%	0	58.8s
0.6	0.86%	0	59.4s
1.2	1.44%	0	66s

TABLE 5.
OBSERVER RESPONSE CHARACTERISTICS WITH FTC FOR ACTUATOR COMPONENT

Fault Position	Actuator Fault		
	With FTC		
Error Value	Max undershoots	Error Steady State	Settling Time
0.1	0.36%	0	58.5s
0.3	0.54%	0	58.6s
0.6	0.78%	0	59.1s
1.2	1.42%	0	65.5s

D. Estimation Results due to the Effect of Covariance Value Selection used on Kalman Filter Block

The effect of the covariance matrix used affects the response characteristics of the observer's bias error estimation. By changing the process noise covariance value (Q) and the measurement noise covariance value (R) used as written below

$$Q = \begin{bmatrix} 8 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 8 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 8 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 8 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 6 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 6 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 6 \end{bmatrix} X\ 10^{-4}$$

$$R = [8 \quad 0] x 10^{-4}$$

Changes in Q and R values cause changes in the response characteristics of the system. The smaller the Q and R values used the greater the settling time value. Otherwise, the bigger the R_e value used, the greater the settling time value or the system requires a longer time to reach the plant's actual condition value.

E. Observability Test Results

The use of conventional observers requires an observability condition of the error bias to be estimated. As mentioned in chapter 2, the augmentation system of the plant consists of the equation of plant state and error bias of sensors and actuators.

If the states of the augmentation system can be estimated by the observer, then the error bias can be identified and estimated. The matrix of the augmentation system is given in equation (28). However, the observability requirements made the observer structure more complex.

$$\left[\begin{array}{c|c} \multicolumn{1}{c}{C\ O} & I_m \\ \hline \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{n+2m-2} \end{bmatrix} [AB] & \begin{matrix} O \\ O \\ \vdots \\ O \end{matrix} \end{array} \right] \quad (28)$$

Optimization formulation with ℓ_0 norm constraint is derived by applying compressed sensing technique. So that the estimation of the bias error can be used to estimate the component error by a single observer as used in this study. This answers the observability problem encountered in the case of using a single observer to estimate multiple errors with a limited measurement variable (less than the estimated number of errors).

Matrix A_{obs} are the result of the observability matrix and proves the observation problems found in a single observer that can be overcome by the method proposed in this study.

$$A_{aug} = \begin{bmatrix} 0.3679 & 0 & 0 & 0 & 0.6321 & 0 & 0 \\ -0.0013 & 0.9434 & 0.0566 & -0.7772 & -0.0038 & 0.0113 & 0 \\ -0.0382 & 0.3570 & 0.6423 & 4.8994 & -0.0245 & 0.0016 & 0 \\ 0.0024 & 0.0837 & -0.0836 & 0.6924 & 0.0009 & 0.0005 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$C_{aug} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$A_{obs} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0.3679 & 0 & 0 & 0 & 0.6321 & 0 & 0 \\ -0.0382 & 0.3570 & 0.6423 & 4.8994 & -0.0245 & 0.0016 & 1 \\ 0.1354 & 0 & 0 & 0 & 0.8646 & 0 & 0 \\ -0.0273 & 0.9762 & 0.0232 & 6.2618 & -0.0612 & 0.0093 & 1 \\ 0.0498 & 0 & 0 & 0 & 0.9502 & 0 & 0 \\ 0.0028 & 1.4533 & -0.4534 & 3.6905 & -0.0771 & 0.0237 & 1 \\ 0.0183 & 0 & 0 & 0 & 0.9817 & 0 & 0 \\ 0.0253 & 1.5181 & -05175 & -0.7954 & -0.0664 & 0.0413 & 1 \\ 0.0067 & 0 & 0 & 0 & 0.9933 & 0 & 0 \\ 0.0252 & 1.1809 & -0.1799 & -4.2658 & -0.0443 & 0.0572 & 1 \\ 0.0025 & 0 & 0 & 0 & 0.9975 & 0 & 0 \\ 0.0044 & 0.6927 & 0.3079 & -4.7530 & -0.0322 & 0.0681 & 1 \end{bmatrix}$$

$$unobsv = length\ (A_{aug} - rank(Ob) = 1$$

In this study, the variables measured were turbine speed and generator torque. Meanwhile, the estimated variables are sensor error, actuator error, and aerodynamic torque disturbance. So it can be concluded that in this study, the use of the proposed method is able to overcome the problem of observation where the number of estimated variables is more than the measurement variable.

IV. CONCLUSIONS

Based on the results that have been obtained, reviewing the problems and the purpose of this final project, it can be concluded:

- The method used in this study is a single observer with optimization of ℓ0 norm constraint that able to overcome the observability problem in estimating the bias fault in wind turbine generator system components.
- The response characteristic to the actuator fault are 0.1, 0.3, 0.6 and 1.2pu, system with FTC yields the maximum undershoot of 0.36, 0.54, 0.78, 1.42% while the system without FTC resulting in a maximum undershoot value of 0.40, 0.58, 0.64 and 1.44%. Error steady state is 0% and settiling time for system with FTC are 58.5, 58.6, 59.1, 65.5s, while the settling time for system without FTC are 58.6, 58.8, 59.4, 66s. The response characteristic with FTC to sensor fault resulting in a maximum undershoot value of 1.6, 2.2, 3, and 4%. Error steady state is 0 and settling time are 63.9, 64.1, 70 and 70.7s. While the system without FTC on sensor fault resulting in maximum undershoot value of 6.2, 10.2, 16.2 dan 26.2%. The settling time is 0s or do not return to the actual state.

V. ACKNOWLEDGMENT

The authors would like to thank the Penelitian Laboratorium ITS 2019 for funding this research and Laboratorium Fisika Rekayasa Dept. Engineering Physics, Faculty of Industrial Technology and System Engineering for providing the facility

REFERENCES

[1] F. Pozo, Y. Vidal, and J. Serrahima, "On Real-Time Fault Detection in Wind Turbines: Sensor Selection Algorithm and Detection Time Reduction Analysis," *Energies*, vol. 9, no. 7, p. 520, 2016.

[2] M. S. Shaker, "Active Fault-Tolerant Control of Nonlinear Systems with Wind Turbine Application," University of Hull, October, 2012.

[3] H. Noura, D. Theilliol, J.-C. Ponsart, and A. Chamseddine, *Fault-tolerant control systems: Design and practical applications*. Springer Science & Business Media, 2009.

[4] Q. Zhao, *Fault tolerant control systems design*. Faculty of Graduate Studies, University of Western Ontario, 1999.

[5] H. Alwi, C. Edwards, and C. P. Tan, *Fault detection and fault-tolerant control using sliding modes*. Springer Science & Business Media, 2011.

[6] C. Nie, "Observer-based robust fault estimation for fault-tolerant control." University of Hull, 2012.

[7] R. J. Patton and S. Klinkhieo, "Actuator fault estimation and compensation based on an augmented state observer approach," *Proc. 48h IEEE Conf. Decis. Control held jointly with 2009 28th Chinese Control Conf.*, 2009, pp. 8482–8487.

[8] M. Ichikawa, N. Sebe, K. Suyama, and K. Indriawati, "A bias fault estimation of actuators and sensors by optimization with ℓ0norm constraint," *2017 Asian Control Conf. ASCC 2017*, pp. 1443–1448.

[9] B. Li, K. Qin, B. Xiao, and Y. Yang, "Finite-time extended state observer based fault tolerant output feedback control for attitude stabilization," *ISA Trans.*, vol. 91, pp. 11–20, 2019.