Fault-Tolerant Control of Wind Turbines using a Takagi-Sugeno Sliding Mode Observer

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Abstract. In this paper, observer-based fault-tolerant control schemes for actuator and sensor faults are implemented within dynamic wind turbine simulations. The faults are directly reconstructed by means of a Takagi-Sugeno sliding mode observer. As simulation models, both a reduced-order model with 4 degrees of freedom and the aero-elastic code FAST by NREL are used. A fault-tolerant control scheme is set up by subtracting the reconstructed fault from the faulty control signal respectively sensor value. With these fault compensation schemes, the corrected controller behaviour is close to the fault-free case. The global stability of the controller in the full-load region in the presence of faults and with active fault compensation is shown by analysing the derivative of an appropriate Lyapunov function.

1. Introduction
The recent years have seen a growing research interest in fault diagnosis and fault-tolerant control for wind turbines, in part triggered by the need to develop more intelligent fault diagnosis systems especially for offshore wind turbines, where availability is a more critical issue due to their reduced accessibility. The fault diagnosis schemes currently employed in wind turbines are typically on the level of the supervisory control, where commonly used strategies include sensor comparison, model comparison and thresholding [1]. These strategies enable a safe turbine operation, which involves shutdowns in case of critical faults, but no intelligent fault-tolerant turbine control on the operational control level.

In the recent years, advanced fault diagnosis methods have been successfully applied in wind turbine simulation studies. In [2], the results of a wind turbine FDI (fault detection and isolation) competition are summarised, where several actuator and sensor faults had to be detected within a pre-defined benchmark model [3]. The presented solutions range from data-driven to observer-based methods. Most of these solutions rely on the evaluation of residuals, which is a standard technique in FDI methods [4]. However, residuals yield no direct fault reconstructions or estimates including the magnitude and "direction" of the faults. For a thorough fault diagnosis of wind turbines, such estimates are important, in order to have an idea about the kind and severity of a fault. Moreover, a direct reconstruction of a fault would be the most valuable information to be used in fault-tolerant control (FTC) schemes.

When it comes to fault-tolerant control for wind turbines, different approaches have also been applied and tested with the benchmark model [3]. In [5], an FTC scheme is set up based on a bank of Unknown Input observers. However, each single fault scenario requires...
a different observer design. In [6], a fast adaptive fuzzy estimator is used to achieve a fault-tolerant behaviour in the partial load region. In [7], a parameter estimation scheme is used for obtaining fault estimates, which are then utilised for fault-tolerant control. Though parameter estimation schemes are well suitable for parametric faults, for other actuator and sensor faults they have some disadvantages like slow reaction to incipient faults and difficult fault isolation. Moreover, the detection and isolation of multiple faults is difficult [4].

In the works mentioned above, all simulations were conducted using the benchmark model [3], which is a reduced-order model. To achieve a more realistic test scenario, some recent papers utilised the modified benchmark model [8], where simulations are carried out within the aero-elastic code FAST [9] by NREL. However, these publications do not present fault reconstruction approaches but are based on residual evaluation for FDI. In [10], a Fuzzy Modelling and Identification (FMI) technique is applied to achieve FTC. However, the algorithm requires an initial training with a pre-defined dataset, which seems cumbersome. Also, for a real turbine, there would be no pre-defined dataset available, due to the stochastic wind behaviour. In [11], a projection-based approach for wind turbine FTC is presented but no FDI module and thus no explicit fault reconstruction. In [12], a Youla parameterisation of stabilising controllers is used with an embedded residual generator for fault detection. Again, no reconstruction of faults is implemented.

In this work, an FTC scheme for actuator and sensor faults in wind turbines is presented based on direct fault reconstruction by means of a Takagi-Sugeno sliding mode observer (TS SMO), which is a nonlinear extension of the Edwards-Spurgeon observer for fault reconstruction [13, 14] and was introduced in [15, 16]. In [17], an extension to the TS SMO from [15] was presented, which involves a weighted switching action that allows a simultaneous reconstruction of faults of significantly differing orders of magnitudes. This concept was applied in [18] to achieve fault-tolerant control for wind turbines in the presence of actuator faults in the pitch angle and generator torque. Using the TS SMO for fault reconstruction also has the advantage that several types of faults (additive, scaling, stuck faults) can be reconstructed with one and the same observer and directly applied for fault compensation.

In this paper, the TS SMO is applied for the first time to achieve sensor fault-tolerant control for wind turbines. Additionally, another example for actuator fault- tolerant control is included as well as a stability analysis in the presence of faults, which was not yet conducted in [18]. As a simulation model, the NREL 5 MW reference turbine [19] is used. Example simulations are carried out within FAST and a reduced-order wind turbine model.

This paper is organised as follows. In section 2, the observer-based fault reconstruction method using a Takagi-Sugeno sliding mode observer is introduced. Sections 4 and 5 contain the main parts of this work. In section 4, the actuator fault compensation strategy is introduced and an example simulation with a pitch actuator scaling fault is presented. In section 5, the fault compensation strategy for sensor faults is described and simulations including a generator speed sensor offset fault are presented using both the reduced-order model and FAST.

2. Sliding Mode Observer Based Fault Reconstruction

Edwards and Spurgeon have introduced a sliding mode observer concept, where actuator and sensor faults can be directly reconstructed by evaluating the so-called equivalent output injection signal [13, 14].

2.1. Takagi-Sugeno Sliding Mode Observer

In this paper, the TS SMO introduced in [15, 16] is used for fault reconstruction, which is a nonlinear extension of the Edwards-Spurgeon observer. The methods for fault reconstruction can thus be employed in a similar way.
In the most general form, the TS SMO design is based on a nonlinear TS system [20] subject to external disturbances $\xi$, actuator faults $f_a$ and sensor fault $f_s$, which is essentially the TS modified form of the basic state-space model normally assumed for FDI problems [4]:

$$\dot{x} = \sum_{i=1}^{N_r} h_i(z) \left( A_{i1} x + B_{i1} u + D_{i1} \xi + F_{i1} f_a \right), \quad \dot{y} = y + f_s = C x + f_s, \quad (1)$$

where $N_r$ denotes the number of distinct nonlinearities. The TS membership functions $h_i$ fulfill the condition $\sum_{i=1}^{N_r} h_i = 1$ and the premise variables $z$ may depend on system states, inputs, and external variables [21].

**Transformed Form of the TS SMO** The TS SMO is designed in a transformed system, where the measurable system states $y$ and the non-measurable system states $x_1$ are separated. This separation is achieved by a transformation $T_c = [N_r \ C]^T$, where $N_r$ denotes the null-space of $C$. With a series of transformations $T_i = T_{L,i} T_{D,i} T_{c}(\text{see} \ [13, 15, 16] \ \text{for a description of the transformation matrices and the transformed system matrices})$, the TS system is brought into a structure where the uncertainties and faults only act on the measurable system states $[15]$

$$\dot{x}_1 = \sum_{i=1}^{N_r} h_i(z) \left( A_{11,i} x_1 + A_{12,i} y + B_{1,i} u \right), \quad (2)$$

$$\dot{\hat{y}} = \sum_{i=1}^{N_r} h_i(z) \left( A_{21,i} x_1 + A_{22,i} y + B_{2,i} u + D_{2,i} \xi + F_{2,i} f_a \right) + \hat{f}_s, \quad (3)$$

For a stable observer to exist, the disturbances and faults have to be bounded. Also, two other structural conditions have to be fulfilled, which are left out here due to lack of space. Please refer to [13, 15, 16] for details.

The TS sliding mode observer in transformed form is given by

$$\dot{x}_1 = \sum_{i=1}^{N_r} h_i(z) \left( A_{11,i} x_1 + A_{12,i} \hat{y} + B_{1,i} u - A_{12,i} \hat{e}_y \right), \quad (4)$$

$$\dot{\hat{y}} = \sum_{i=1}^{N_r} h_i(z) \left( A_{21,i} x_1 + A_{22,i} \hat{y} + B_{2,i} u - (A_{22,i} - A_{22,i}^s) \hat{e}_y + \nu \right), \quad (5)$$

where $\hat{e}_y := \hat{y} - (y + f_s)$ denotes the output error including sensor faults and $A_{22,i}^s$ is a stable design matrix. In this work, the discontinuous switching term necessary to establish and maintain a sliding motion is given by

$$\nu = \begin{cases} -\rho \left\frac{P_2 W \hat{e}_y}{\|P_2 W \hat{e}_y\|} \right. & (\hat{e}_y \neq 0) \\ 0 & (\hat{e}_y = 0) \end{cases}, \quad (6)$$

Here, $P_2$ is the symmetric, positive definite solution of the Lyapunov equation

$$P_2 A_{22,i}^s + A_{22,i}^{sT} P_2 = -Q_2, \ \text{where} \ Q_2 \ \text{is a symmetric positive definite design matrix. Expression (6) differs from the discontinuous switching terms in [13] and [15, 16] in that the output error vector $\hat{e}_y$ is modified with a diagonal weighting matrix $W$ and that a diagonal gain matrix $\rho = \text{diag}(\rho_1 \cdots \rho_p)$ is used instead of a scalar gain factor. The elements of the weighting matrix are the reciprocal values of the estimated maximum values of the output vector:}$$
\( W = \text{diag}(W_1 \cdots W_p) = \text{diag}(1/|y_{\text{max},1}| \cdots 1/|y_{\text{max},p}|) \). The modified switching function (6) was introduced in [17] to enable a simultaneous reconstruction of both pitch angle and generator torque actuator faults, which have significantly differing orders of magnitude.

**Equivalent Output Injection Signal** Similarly to the equivalent control action in sliding mode control structures, for sliding mode observers the so-called equivalent output injection signal describes the average behaviour of the discontinuous component \( \nu \) [14].

The equivalent output injection signal is a measure for the effort to maintain the sliding motion [14] and can be obtained as a continuous approximation of the discontinuous component (6) by introducing a small positive scalar \( \delta \):

\[
\nu_{\text{eq}} = -\rho \frac{P_2 W \hat{e}_y}{\|P_2 W \hat{e}_y\| + \delta},
\]

(7)

2.2. Fault Reconstruction
If faults occur in the system, a higher effort needs to be exerted to maintain the sliding motion, which is then reflected in the equivalent output injection signal \( \nu_{\text{eq}} \). In [13, 14], direct fault reconstruction methods for actuator as well as sensor faults are described based on evaluating this signal. For a TS sliding mode observer, these methods can be adapted and used in a similar fashion [15, 16]. If no sensor faults are present and neglecting disturbances, actuator faults can be reconstructed using the relation [16]

\[
\hat{f}_a = \sum_{i=1}^{N_r} h_i(z) \mathcal{F}_2^+ \nu_{\text{eq}},
\]

(8)

where \( \mathcal{F}_2^+ \) denotes the left pseudo-inverse of the transformed actuator fault matrix \( \mathcal{F}_2 \).

For sensor fault reconstruction, the method introduced by Tan and Edwards [22] is used, where sensor faults can be treated as actuator faults within an augmented system and the fault reconstruction then works analogously to (8).

3. Wind Turbine Models
The simulations in this work are carried out with the aero-elastic code FAST [9] by NREL and the parameters of the NREL 5 MW reference [19] turbine are used throughout. For actuator faults, a good quality of fault reconstruction and fault compensation could be achieved within FAST simulations. For generator speed sensor faults, the quality of the fault reconstruction and thus the quality of fault compensation within FAST simulations is reduced compared to actuator faults. Therefore, simulations are also carried out using a reduced-order model with four degrees of freedom, for the sake of comparison. This reduced-order model (see for example [23]), was adapted for the NREL 5 MW turbine and transformed into TS form in [24] and is omitted here for the sake of brevity. It is a standard model including a torsion-flexible drivetrain as well as a fore-aft tower top and a flapwise blade-tip degree of freedom. The TS SMO design was based on a further reduced-order model containing only the drivetrain degrees of freedom [17, 18], which proved a suitable choice for achieving good fault reconstruction results.

**Remark on Measurement Noise** In many papers on wind turbine FDI, as in [8], it is assumed that adding white noise to the sensor signals leads to more realistic scenarios. This, however, is not the case, as a realistic simulation would demand a precise knowledge of each sensor and its measuring quality. From one of the author’s working experience with a wind turbine manufacturer, all important measurements utilised in the present work (rotor and generator...
speed, pitch angle, generator torque), are virtually noise free. It was thus decided to omit measurement noise in this work.

What is present in wind turbines however, is one characteristic frequency imposed on the generator speed signal due to the periodic rotor excitation of the drive train. When using the generator speed as a controlled variable, a notch filter thus needs to be applied to smooth the generator speed signal. Such a notch filter is routinely applied in industrial wind turbine control [25] and was also applied for the FAST simulations in section 5 in this work, where the generator speed was used as controlled variable. For the rotor speed measurement, a simplifying assumption was made here that it is a continuous signal, which is justified for the present purpose of validating the basic fault reconstruction facilities. In most current wind turbines, the rotor speed signal is discretised, due to the limited number of metal pieces on the main shaft that are scanned by a magnetic sensor, although better sensing technologies, which could yield nearly continuous signals, are already available, like optical scanning of densely spaced barcodes.

4. Actuator Fault-Tolerant Control

4.1. Fault Compensation

If faults occur in the system, provided that these faults can be accurately reconstructed, the most straightforward strategy to achieve fault-tolerance is a simple fault compensation method, whereby the reconstructed faults are subtracted from the demanded control input:

$$u_{\text{corr}} = u - \hat{f}_a.$$  \hspace{1cm} (9)

In order to avoid feeding back initial transients, the components of $\hat{f}_a$ are set to zero during the first 20 seconds of the simulation. In some cases it might also be necessary to filter the reconstructed fault signals before using them in the fault compensation. After applying the correction (9), the actual input signal that acts on the system is given by

$$\tilde{u}_{\text{corr}} = u_{\text{corr}} + f_a = u + (f_a - \hat{f}_a).$$  \hspace{1cm} (10)

It is plain to see that the quality of the fault compensation depends on the quality of the fault reconstruction. If $\hat{f}_a$ were a perfect reconstruction of $f_a$, $\tilde{u}_{\text{corr}}$ would exactly correspond to the original faultless control signal $u$.

4.2. Other Fault Types

The fault reconstruction (8) by means of evaluating the equivalent output injection signal always yields an additive fault component $f_a$. If faults of other types occur, like scaling faults, these can be reconstructed by tracing them back to the additive fault structure.

For example, for a scaling fault in one actuator, with a (faulty) scaling constant $\alpha$, the actual input signal after correction and fault would be given by $\tilde{u}_{\text{corr}} = u_{\text{corr}} + f_a = \alpha u_{\text{corr}}$, such that the faulty scaling constant could be reconstructed from the reconstructed additive fault component: $\hat{\alpha} = \frac{u_{\text{corr}} + f_a}{u_{\text{corr}}}$. However, for fault compensation, always the additive fault component is used.

4.3. Simulation Example

As an example for actuator fault-tolerant control, a pitch angle scaling fault with a faulty scaling constant of $\alpha = 0.2$ was simulated by gradually introducing the fault with a linear ramp between 30 s and 70 s. In Figure 1, the results for the states $\omega_r$ and $\beta$, as well as for the demanded (corrected) pitch angle $\beta_{d,\text{corr}}$, are depicted for the fault-free case, the faulty case without fault compensation, and the faulty case with active fault compensation.

It can be seen from Figure 1 that with active fault compensation the scaling fault with $\alpha = 0.2$ is fairly well compensated for, such that the system behaviour comes close to the behaviour in
4.4. Stability Analysis

To analyse the stability of the fault-tolerant control scheme, the derivative of a suitable Lyapunov function is investigated. The stability of a nonlinear system in general is ensured if a Lyapunov function can be found [26]. Two prerequisites have to be fulfilled for a function $V(x)$ to be a Lyapunov function: 1. $V(x) > 0$ for all values of $x$. 2. The derivative of $V(x)$ must be negative: $\dot{V}(x) < 0$. In particular, these two conditions are fulfilled for a quadratic Lyapunov function $V = x^T P x$, with a symmetric, positive definite matrix $P$.

In this paper, the stability analysis is restricted to the full-load region, where the pitch angle is the sole actuator. As a controller, the PDC (parallel distributed compensation) controller presented in [18] is used. It is based on a rigid drivetrain model, where only two states, the rotor speed $\omega_r$ and the pitch angle $\beta$ are included. Taylor linearised models around several stationary points are then calculated, and for each local model, an LQR control design is conducted. The local linearised models can be combined into a TS system that describes the approximated dynamics in the full-load region:

$$\dot{x} = \sum_i^{N_r} h_i(\beta) \left( A_i \Delta x_i + B \Delta u_i + E_i \Delta v_i \right), \quad (11)$$

where $x = (\omega_r, \beta)^T$ denotes the system vector, $A_i, B$ and $E_i$ denote the linearised system, input and disturbance matrices, respectively. Here, triangular TS membership functions $h_i(\beta)$ are used that depend solely on the pitch angle as scheduling variable. Note that these membership functions differ from those for the TS SMO, which were obtained using the sector-nonlinearity approach [17, 21]. The difference terms are given by $\Delta x_i = x - x_i$, $\Delta u_i = \beta_d - \beta_i$, $\Delta v = v - v_i$. 

Figure 1: FAST simulations with turbulent wind input (mean windspeed: 18 m/s, turbulence intensity: 15 % (NTM), Kaimal model) and incipient pitch angle scaling fault (final faulty scaling value: $\alpha = 0.2$). Black lines: fault-free case; green lines: faulty case without fault compensation; red: faulty case with active fault compensation.
The PDC control law is given by

$$u = \beta_d = - \sum_{i}^{N_r} h_i(\beta) k_i^T \Delta x_i - k_I x_I = - \sum_{i}^{N_r} h_i(\beta) k_i^T \Delta y_i - k_I x_I,$$

(12)

where an integrator state $x_I = \int_{0}^{\tau} d\tau (\omega_r - \omega_{\text{ref}})$ was included. Here, the state vector $x$ is equal to the output vector $y$, as both the rotor speed and the pitch angle are measurable. The controller gains are given by $k_i^T = (k_{\omega_r,i} \quad k_{\beta,i})$. $k_I$ denotes the controller gain for the integrator state, which is independent of the current values of the membership functions $h_i(\beta)$.

**Input-to-State Stability** The approximated model (11) is a TS model with an external bounded disturbance $\sum_i^{N_r} h_i(\beta) E_i v$ and can be written as

$$\dot{x} = \sum_i^{N_r} h_i(\beta) (A_i x + B u + a_i) + \sum_i^{N_r} h_i(\beta) E_i v,$$

(13)

with the affine term $a_i = -A_i x_i - B u_i - E_i v_t$. For TS systems with bounded external inputs, the input-to-state stability [27] is ensured if the Lyapunov stability of the autonomous TS system can be shown [28]. Therefore, in the following, a Lyapunov stability analysis will be conducted for the autonomous TS system $\dot{x} = \sum_i^{N_r} h_i(\beta) (A_i x + B u + a_i)$. Defining $b_i := -(k_{\omega_r,i} \omega_{\text{ref}} + k_{\beta,i} \beta_i)$, the control law can be written as $u_{\text{corr}} = -\sum_i^{N_r} h_i(\beta) (k_i^T x + b_i) - k_I x_I$. Introducing $A_i,CL := A_i - B k_i^T$ and the affine term $g_i := a_i - B b_i$, the closed-loop system can be written as $\dot{x} = \sum_i^{N_r} h_i(\beta) (A_i,CL x + g_i)$. Including faults and active fault compensation, the system is modified by an additional term $\Delta_f := f_a - \hat{f}_a$:

$$\dot{x} = \sum_i^{N_r} h_i(\beta) (A_i,CL x + g_i) + B \Delta_f.$$

(14)

Let $V(x) = x^T P x$ be a candidate Lyapunov function for the closed-loop system (14). Then it is obvious that $V > 0$ holds. It must now be shown that $\dot{V} < 0$ is fulfilled. $\dot{V}$ is given by

$$\dot{V} = 2 \sum_i^{N_r} h_i(\beta) x^T (P A_i,CL + P g_i - P B k_I x_I) + 2 x^T P B \Delta_f.$$

(15)

The common Lyapunov matrix $P$ can be found by solving a linear matrix inequality (LMI) (see [18]). The complete term $\dot{V}$ was simulated for the above pitch actuator scaling fault example for the fault free case and for the faulty case with active fault compensation (see Figure 2), where it can be seen that even in the presence of a fault and with active fault compensation, $\dot{V}$ is well below zero for the whole simulation time. This analysis does not constitute a formal proof of stability, since it was only conducted for one particular simulation run. However, when analysing $\dot{V}$ for other turbulent simulations with different mean wind speeds, it can be found that the negativity is also ensured, which is left out here due to lack of space.

### 5. Sensor Fault-Tolerant Control

Using the reconstructed sensor faults $\hat{f}_s$, a sensor fault-tolerant control scheme can be implemented by substracting the reconstructed sensor faults from the (faulty) outputs:

$$y_{\text{corr}} = C x + (f_s - \hat{f}_s).$$

(16)
Again, the quality of the fault compensation is determined by the quality of the fault reconstruction, i.e., whether the difference $f_s - \hat{f}_s$ is close to zero.

As an example, an incipient generator speed sensor offset fault with a final fault value of 0.2 rad/s was simulated using both the 4-DOF model (see Figure 3) and FAST (see Figure 4). In the first case, the reference simulation wind speed was used as input for the TS SMO, whereas for the FAST simulation, a reconstructed wind speed using a TS Luenberg observer [29] was used. In both cases, the generator speed was used as controlled variable instead of the rotor speed.

### 5.1. Simulation Example

![Figure 3](image-url)  

Figure 3: Turbulent simulations of the 4-DOF model (mean wind speed: 18 m/s) with incipient offset fault of the generator speed sensor. Black lines: fault-free case; green lines: faulty case without fault compensation; red lines: faulty case with active fault compensation.

One can see that in the reduced-order model simulation, the achieved sensor fault reconstruction is quite precise. The small offset between the actual and the reconstructed fault can theoretically be reduced to zero by decreasing the parameter $\delta$ in the equivalent output injection signal ($\delta \to 0$). However, in this case, the simulation step size would also have to decreased ($\Delta t \to 0$), which poses a practical limit.

Due to the precise sensor fault reconstruction, very good results for the fault-tolerant control are also achieved. However, in the FAST simulation, the quality of the sensor fault reconstruction is reduced. The mean fault value is still reasonably well reconstructed, but the signal is superimposed with considerable noise. As a consequence, the fault compensation within the FAST simulation is of reduced quality compared to the reduced-order model simulation. However, compared to the case without any fault compensation, the simple sensor fault-tolerant control scheme (16) still achieves a reasonable fault compensation (see Figure 4a).
Figure 4: Turbulent FAST simulation (mean wind speed: 18 m/s) with incipient offset fault of the generator speed sensor. Black lines: fault-free case; green lines: faulty case without fault compensation; red lines: faulty case with active fault compensation.

5.2. Stability Analysis
A stability analysis can be conducted similarly to the case of actuator fault-tolerant control (see section 4.4), the only difference being a slightly modified term $\dot{V}$:

$$\dot{V} = 2 \sum_{i} h_i (\beta) x^T (P A_{i,CL} + P g_i - P B k_f x_I - P B u_{F,i}) ,$$

with $u_{F,i} := k_{\omega_g,i} f_{s,\omega_g} + k_f \int_0^t \Delta f_{s,\omega_g} \, dt$ and $\Delta f_{s,\omega_g} := (f_{s,\omega_g} - \hat{f}_{s,\omega_g})$.

In Figure 5, $\dot{V}$ is depicted for the described generator speed sensor fault with active fault compensation for three turbulent simulations (using both the 4-DOF model and FAST) with different mean wind speeds, representative of the full load region. It can be seen that $\dot{V}$ is negative in all three cases. Again, this does not constitute a general proof of stability, but it gives very good theoretical support that the stability is still ensured using the presented sensor fault-tolerant control scheme.

Figure 5: Derivatives of Lyapunov function for turbulent simulations with incipient offset fault (final value 0.2 rad/s) of the generator speed sensor with active fault compensation. blue lines: simulations with 4-DOF model; red lines: FAST simulations.

6. Conclusion
In this paper, actuator and sensor fault-tolerant control schemes for wind turbines were presented based on direct fault reconstruction by means of a Takagi-Sugeno sliding mode observer. In each case, one example fault was simulated using the aero-elastic code FAST. For the pitch actuator fault example, very good results are achieved, were the behaviour in the faulty case with active fault compensation is similar to the fault-free case. In the case of the generator speed sensor fault, the fault compensation quality is reduced in FAST simulations, yet a still reasonable fault-tolerant behaviour is achieved. The presented fault reconstruction and FTC schemes could be
implemented as well on a real wind turbine, although some extensions and modifications would have to be done like a discrete implementation of the TS observer and a decision algorithm to confirm the fault compensation action.

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