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Fault-Tolerant Control of Doubly-Fed Wind Turbine Generation Systems under Sensor Fault Conditions

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Abstract: This paper studies the fault-tolerant control problem of uncertain doubly-fed wind turbine generation systems with sensor faults. Considering the uncertainty of the system, a fault-tolerant control strategy based on a T-S fuzzy observer is proposed. The fuzzy observer is established based on the T-S fuzzy model of the uncertain nonlinear system. According to the comparison and analysis of residual between the state estimation of the fuzzy observer output and the measured value of the real sensor, a fault detection and isolation (FDI) based on T-S fuzzy observer is designed. Then by using a Parallel Distributed Compensation (PDC) method we design the robust fuzzy controller. Finally, the necessary and sufficient conditions for the stability of the closed-loop system are proved by quoting Lyapunov stability theory. The simulation results verify the effectiveness of the proposed control method.

Keywords: fault-tolerant control; wind turbine generation system; uncertainty; nonlinearity; T-S fuzzy

1. Introduction

With the continuous progress of social economy, humans' demands and dependence on energy have reached the commanding heights of history, and the development of green energy has become a topic of widespread concern around the world [1–3]. Wind power energy as an important component of green energy has become an important force to maintain the sustainable development of global energy [4]. As a typical large-scale complex nonlinear system, the safe and stable operation of wind turbines is threatened due to their poor installation environment, which leads to frequent sensor and actuator faults, and also affects the process of extensive engineering of wind turbine generation systems. Therefore, as an effective means to improve the safety and reliability of wind power system, fault-tolerant control has become a research hotspot.

There are many kinds of sensors in doubly-fed wind turbine generation systems, and their accuracy, timeliness and reliability are very important for the stable operation of the closed-loop system. Once a fault occurs, the feedback controller can't get the correct feedback data information, which will affect the overall control performance of the system, and even lead to complete system paralysis. In recent years, many fault diagnosis and fault-tolerant control methods for sensor faults have been put forward by experts and scholars at home and abroad [5–7]. In [8], a sliding mode observer is used to detect sensor faults in a permanent magnet synchronous motor drive system. For current and voltage sensor faults, fault-tolerant control strategies of closed-loop V/f and direct calculation of counter potential were proposed, respectively. In [9], a nonlinear observer is introduced for the angular rate and attitude sensor faults of the satellite attitude control system, and an integrated sensor fault detection and recovery control method is proposed. In the study of sensor faults in doubly-fed wind power generation systems, a fault-tolerant control strategy based on Kalman filter is studied in [10].

During the sensor fault period of the system, the estimated value of the Kalman filter output is used to replace the measured value of the faulty sensor, and the vector control system is reconfigured to achieve the fault-tolerant control purpose. Reference [11] studied a fault diagnosis method for the high-speed shaft speed sensors of wind turbine generation systems by designing a fuzzy T-S system sliding mode observer, but no specific control method was given to compensate the reconstruction faults.

Wind turbine generation systems are strong non-linear systems, which often show stochastic and switching characteristics under the action of stochastic and intermittent winds. In practical engineering applications, it is usually difficult to achieve the desired control effect with a controller based on a traditional linear observer. The T-S fuzzy algorithm has the advantages of simple structure and strong approximation, the model output has good mathematical expression characteristics, which can approximate almost any complex nonlinear system, hence uncertain nonlinear system controllers based on the T-S fuzzy model have been widely used in engineering [12–14]. In order to maximize the energy capture, a variable structure sliding mode controller (SMC) for a doubly-fed wind turbine was designed on the basis of fuzzy logic theory in [15]. A T-S fuzzy model was used in [16] to describe nonlinear systems, and a Robust Fuzzy Scheduler Controller (RFSC) was designed to achieve the stability of the system by taking into account the parameter uncertainty of the system and wind disturbance. Reference [17] also established a complete wind turbine pitch model based on fuzzy theory, and designed a fuzzy proportional-integral-derivative (PID) controller to realize real-time control of wind energy systems. However, the possibility of failure of wind energy system components is inevitable in practice, hence the stability of the system will be difficult to guarantee once a failure of wind turbine components occurs.

Here, a fault tolerant control strategy based on a T-S fuzzy observer is studied for sensor faults of doubly-fed wind turbine generation systems. Firstly, the uncertain T-S fuzzy model of a nonlinear system is established considering the uncertainty of the system. Secondly, the fault detection and isolation (FDI) based on T-S fuzzy observer is designed. The state estimation value of the fuzzy observer output is compared with the real sensor measurement values to analyze the residual. The state reconstruction of the output based on normal sensor and observer is selected by a decision module and switcher. Then, a robust fuzzy controller is designed by using a Parallel Distributed Compensation (PDC) method to realize fault tolerant control of sensor faults in uncertain nonlinear systems. Finally, the feasibility of the proposed method is proved by quoting Lyapunov stability theory, and the simulation results further verify the effectiveness of the control method.

2. Problem Description

The fuzzy rules of the fuzzy system T-S model (1) is established with sensor faults and parameter uncertainties, each of which represents one of the subsystems.

R^i: If $z_1(t)$ is F_1^i and $z_2(t)$ is $F_2^i \ldots$ and $z_k(t)$ is F_k^i, then:

$$\begin{array}{ll} \dot{x}(t) = (A_i + \Delta A_i)x(t) + B_i u(t) & \\ y(t) = C_i x(t) + \overline{F}_i f_s(t) & i = 1, 2, \ldots, r \end{array} \tag{1}$$

where R^i denotes the i-th fuzzy rule, $z(t) = [z_1(t)\ z_2(t) \ldots z_k(t)]^T$ represents the premise variable, F_j^i stands for fuzzy set, $i = 1, 2 \ldots r$ denotes the total number of system fuzzy rules, $j = 1, 2 \ldots k$; $x(t) \in R^n$ is the state vector, $u(t) \in R^m$ is the control input, $y(t) \in R^p$ is the system output; $A_i \in R^{n\times n}$, $B_i \in R^{n\times m}$ and $C_i \in R^{p\times n}$ represent the parameter matrices of the system respectively. $\overline{F}_i \in R^{p\times q}$ denotes the known sensor fault matrix, $f_s(t) \in R^{q\times 1}$ is sensor fault, ΔA_i is the uncertainty real value matrix, assuming that $f_s(t)$ and ΔA_i are norm bounded, and there are positive numbers α and β, which make inequalities $\|f_s(t)\| < \alpha$, $\|\Delta A_i\| < \beta$ valid.

Defining fuzzy weights:

$$u_i(z(t)) = \frac{h_i(z(t))}{\sum_{i=1}^{r} h_i(z(t))} \tag{2}$$

where $h_i(z(t)) = \prod_{j=1}^{k} F_j^i(z_j(t))$, $F_j^i\big(z_j(t)\big)$ denotes the membership function of the premise variable $z_j(t)$ corresponding to fuzzy value. $h_i(z(t))$ denotes the weight of rule i and meets the following conditions:

$$\begin{array}{ll} h_i(z(t)) \geq 0, & \sum_{i=1}^{N} h_i(z(t)) > 0, \quad i = 1, 2, \ldots, r \\ 0 < u_i < 1, & \sum_{i=1}^{Nr} u_i(z(t)) = 1 \end{array}$$

After defuzzification the equation of state of the whole fuzzy T-S system can be given by:

$$\begin{aligned} \dot{x}(t) &= \sum_{i=1}^{r} u_i(z(t))[(A_i + \Delta A_i)x(t) + B_i u(t)] \\ y(t) &= \sum_{i=1}^{r} u_i(z(t))[C_i x(t) + \overline{F}_i f_s(t)] \end{aligned} \tag{3}$$

Without loss of generality, in order to design the output feedback control law based on T-S fuzzy observer, the Equation (3) is transformed into the following form:

$$\begin{aligned} \dot{x}(t) &= \sum_{i=1}^{r} u_i(z(t))[(A_i + \Delta A_i)x(t) + B_i u(t)] \\ y(t) &= \sum_{i=1}^{r} u_i(z(t))(I + F)C_i x(t) \end{aligned} \tag{4}$$

where I represents the identity matrix, $F = diag\big(f_1, f_2, \ldots, f_p\big)$, $-0.1 \leq f_a(x(t)) \leq 0.1$, $a = 1, 2, \ldots, p$ represents the sensor fault model matrix and considers it normally bounded.

3. FDI Design Based on T-S Fuzzy Observer

Figure 1 depicts the overall structure block diagram of sensor fault-tolerant control in wind power generation system, in which the FDI based on T-S fuzzy observer consists of the following two steps:

(1) The output residual of the system is produced according to the designed T-S fuzzy observer, and the output signal of the sensor is taken as the input signal of the fuzzy observer. Then the observation value of the observer is compared with the actual sensor output and the residual error is calculated.

(2) The residual R_{res1} and R_{resg} are compared with the residual threshold R_{th}, which are fuzzy observer1 and the output residuals of the fuzzy observer g, respectively. The logic division of the residual error is used to judge whether the system has sensor fault. Finally, the state reconstruction of the output based on normal sensor and observer is selected by the decision module and switcher.

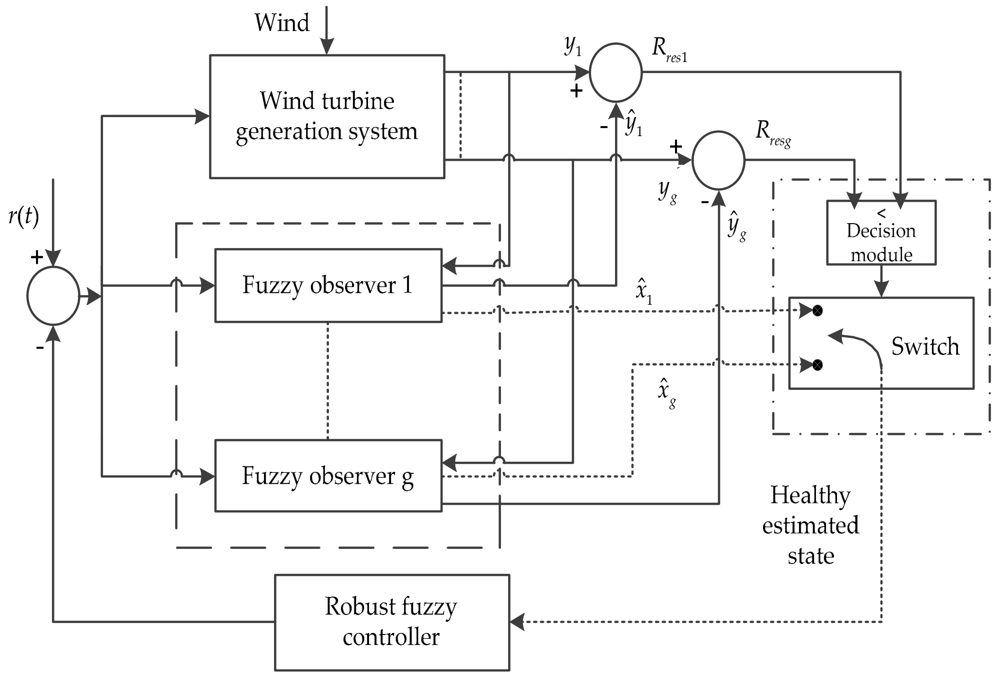


Figure 1. Overall structure of sensor fault tolerant control in wind turbine generation system.

Residual $R_{res}(t)$ is the measurable output deviation, namely:

$$R_{res}(t) = e_y(t) = y(t) - \hat{y}(t) \tag{5}$$

The threshold value R_{th}:

$$R_{th} = \sup_{fault-free} ||R_{res}(t)||_{peak} \tag{6}$$

Then the corresponding fault decision logic is:

$$||R_{res}(t)|| \begin{cases} \leq R_{th} \text{ no sensor failure} \\ > R_{th} \text{ sensor failure} \end{cases}$$

Assuming that at most one sensor fails at any given time. If $|R_{res1}| > |R_{res2}|$, we switch to observer 2, otherwise we switch to observer 1 and so on. When the sensor works normally, the residual error affected by its noise will not converge to zero. In order to avoid false alarms, the threshold must be set large enough [18].

It is assumed that the state of the system model (1) is observable, adopting the same rule prerequisites as Equation (1) T-S fuzzy model (4) based on parameter uncertainty and sensor fault, fuzzy observer rules are as follows:

R^i: If $z_1(t)$ is F_1^i and $z_2(t)$ is $F_2^i \ldots$ and $z_k(t)$ is F_k^i, then:

$$\begin{array}{ll} \dot{\hat{x}}(t) = A_i\hat{x}(t) + B_iu(t) + L_i(y(t) - \hat{y}(t)) & \\ \hat{y}(t) = C_i\hat{x}(t) & i = 1, 2, \ldots, r \end{array} \tag{7}$$

where $\hat{x}(t)$ denotes the state estimation of the fuzzy observer, $\hat{y}(t)$ is the output vector, $L_i \in R^{n\times 1}$ is the observer gain matrix. After defuzzification, the output description of the fuzzy observer is given by:

$$\begin{array}{l} \dot{\hat{x}}(t) = \sum\limits_{i=1}^{r} u_i(z(t))[A_i\hat{x}(t) + B_iu(t) + L_i(y(t) - \hat{y}(t))] \\ \hat{y}(t) = \sum\limits_{i=1}^{r} u_i(z(t))C_i\hat{x}(t) \end{array} \tag{8}$$

4. Robust Fuzzy Controller

4.1. State Feedback Controller Design

The local state feedback controller based on T-S fuzzy model (4) is designed using PDC method, then the fuzzy rule for the input of the j-th controller is:

$$\text{Rule}j : \text{If } g_1(t) \text{ is } M_{1j} \text{ and } g_2(t) \text{ is } M_{2j} \ldots \text{and } g_k(t) \text{ is } M_{kj}, \text{ then}$$

$$u(t) = r(t) - K_j\hat{x}(t) \quad j = 1, 2, \ldots, p \tag{9}$$

where $g(t) = [g_1(t), g_2(t), \ldots, g_k(t)]$ represents the premise variable, p represents the total number of fuzzy rules, $K_j \in R^{m\times n}$ denotes the regular feedback gain matrix, $r(t) \in R^{m\times 1}$ is the reference input, After defuzzification, the global state controller of the system can be expressed by:

$$u(t) = r(t) - \sum_{j=1}^{p} u_j(g(t))K_j\hat{x}(t) \tag{10}$$

4.2. Stability Analysis of Nonlinear Closed-Loop Systems

The goal of fault-tolerant control is to design the control rate so that the nonlinear uncertain system is stable and robust to some extent in the event of sensor failure.

Defining the system state observation error:

$$e(t) = x(t) - \hat{x}(t) \tag{11}$$

From Equations (3) and (8), the closed-loop equation of the system can be given:

$$\begin{aligned} \dot{x}(t) &= \sum_{i=1}^{r} u_i(z(t))\Big[(A_i + \Delta A_i)x(t) + B_i(r(t) - \sum_{j=1}^{p} u_j(g(t))K_j\hat{x}(t))\Big] \\ &= \sum_{i=1}^{r}\sum_{j=1}^{p} u_i(z(t))u_j(g(t))\Big[(E_{ij} + \Delta A_i)x(t) + B_iK_je(t) + B_ir(t)\Big] \end{aligned} \tag{12}$$

where $E_{ij} = A_i - B_iK_j$.

Substituting Equation (11) into Equation (5) we get:

$$R_{res}(t) = y(t) - \hat{y}(t) = \begin{cases} \sum_{i=1}^{r} u_iC_ie(t) & \text{if } F = 0 \\ \sum_{i=1}^{r} u_iC_ie(t) + FC_ix(t) & \text{if } F \neq 0 \end{cases} \tag{13}$$

Then the estimated error of state is:

$$\begin{aligned} \dot{e}(t) &= \dot{x}(t) - \dot{\hat{x}}(t) \\ &= \sum_{i=1}^{r} u_i(z(t))[(A_i + \Delta A_i)x(t) + B_iu(t)] \\ &\quad - \sum_{i=1}^{r} u_i(z(t))[A_i\hat{x}(t) + B_iu(t) + L_i(y(t) - \hat{y}(t))] \\ &= \sum_{i=1}^{r}\sum_{j=1}^{p} u_i(z(t))u_j(g(t))[(\Delta A_i - L_iFC_j)x(t) + (A_i - L_iC_j)e(t)] \end{aligned} \tag{14}$$

Combined with Equations (12) and (14), the new fuzzy system can be arranged as follows:

$$\begin{bmatrix} \dot{x}(t) \\ \dot{e}(t) \end{bmatrix} = \sum_{i=1}^{r}\sum_{j=1}^{p} u_i(z(t))u_j(g(t))\begin{bmatrix} H_{ij} & \Delta H_{ij} \end{bmatrix}\begin{bmatrix} x(t) \\ e(t) \end{bmatrix} + \begin{bmatrix} B_i \\ 0 \end{bmatrix} r(t) \tag{15}$$

where $H_{ij} = \begin{bmatrix} E_{ij} & B_iK_j \\ 0 & A_i - L_iC_j \end{bmatrix}$, $\Delta H_{ij} = \begin{bmatrix} \Delta A_i & 0 \\ \Delta A_i - L_iFC_j & 0 \end{bmatrix}$.

Lemma 1: For the sensor fault system (15) with uncertain parameters, if the following matrix inequality:

$$\mu\left[\mathrm{T}H_{ij}\mathrm{T}^{-1}\right] \le -\|\mathrm{T}\Delta H_{ij}\mathrm{T}^{-1}\|_{\max} - \delta, \quad \forall i, j \tag{16}$$

is true, then the system (15) is stable. Where the scalar δ is positive and denotes the robustness index, T is the symmetric matrix of proper dimensional transformation, $\|\mathrm{T}\Delta H_{ij}\mathrm{T}^{-1}\|_{\max}$ denotes the maximum value of $\|\mathrm{T}\Delta H_{ij}\mathrm{T}^{-1}\|$. The proof is detailed in [19].

Let's set the transformation symmetric matrix $T = T^T$, $P = TT$. According to Lyapunov stability theory, if there is a positive definite matrix P and the control rate (10) forms the following inequality:

$$PH_{ij} + H_{ij}^TP < 0, \quad \forall i, j \tag{17}$$

is true, the fuzzy control system (4) is globally asymptotically stable.

In order to obtain observer gain L_i and controller gain K_j for convenience, it is assumed that:

$$P = \begin{bmatrix} P_{11} & 0 \\ 0 & P_{22} \end{bmatrix} \tag{18}$$

Let $M = P_{11}^{-1}$, that is:

$$M = \begin{bmatrix} M_{11} & 0 \\ 0 & I \end{bmatrix} = \begin{bmatrix} P_{11}^{-1} & 0 \\ 0 & I \end{bmatrix} \tag{19}$$

Let $Y_j = K_jM_{11}$, $X_j = P_{22}L_i$, multiply both sides of Equation (17) by matrix $M = P_{11}^{-1}$ to obtain the following linear matrix inequality (LMI):

$$M_{11}A_i^T + A_iM_{11} - (B_iY_j)^T - B_iY_j < 0 \tag{20}$$

$$A_i^TP_{22} + P_{22}A_i - (X_iC_j)^T - X_iC_j < 0 \tag{21}$$

Converting the inequality in the above equation into an equation, then the above inequality becomes:

$$M_{11}A_i^T + A_iM_{11} - (B_iY_j)^T - B_iY_j = -\delta I \tag{22}$$

$$A_i^TP_{22} + P_{22}A_i - (X_iC_j)^T - X_iC_j = -\delta I \tag{23}$$

By solving Equations (22) and (23), the observer gain $L_i(L_i = P_{22}^{-1}X_i)$ and controller gain K_j $(K_j = Y_jM_{11}^{-1})$ can be easily obtained. Figure 2 describes the relationship between the uncertainty and the robustness index of the system, it can be easily seen from which the control system can still run stably under certain conditions despite the great uncertainty.

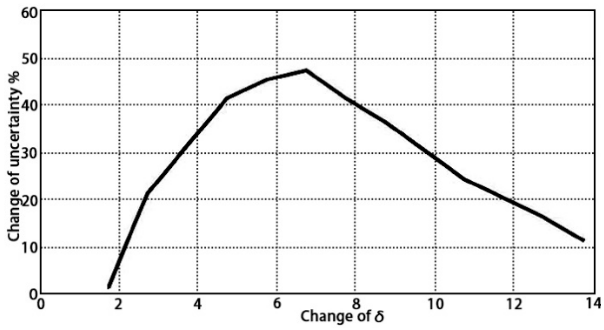


Figure 2. The uncertainty relative to robustness index.

5. Mathematical Model of Wind Turbine Generation System

5.1. Dynamic Equation of Doubly-Fed Wind Turbine Generation System

According to Betz theory, the mechanical power P_{wt} obtained by the wind turbine from the wind can be described by:

$$P_{wt} = 0.5\rho R^2 V^3 C_p(\lambda, \beta) \tag{24}$$

where ρ denotes air density, R denotes the radius of the wind wheel, V denotes the wind speed, λ denotes the tip speed ratio (TSR), β denotes the pitch angle, $C_p(\lambda, \beta)$ represents the conversion efficiency coefficient of wind energy, which is the function of λ and β, the TSR $\lambda = \Omega_r R/V$, Ω_r is the mechanical angular velocity of the wind turbine.

The output torque of the wind turbine T_{wt} can be described by:

$$T_{wt} = P_{wt}/\Omega_r = 0.5\rho R^2 V^3 C_p(\lambda, \beta)/\Omega_r \tag{25}$$

When the wind speed is constant, the mechanical power output of the wind turbine is only related to the wind energy conversion efficiency coefficient C_p. When β remains unchanged, C_p is only related to the TSR λ. For a particular wind turbine, there is and only one optimal TSR λ_{opt},$C_{p\max}$ represents the maximum wind energy capture coefficient. Under the rated wind speed, fixed pitch control $\beta = 0$ is adopted. The maximum capture of wind energy can be achieved by adjusting the electromagnetic torque of the generator to follow the change of wind speed to make it reach the maximum value. when $C_p(\lambda, \beta) = C_p(\lambda)$, $C_{p\max} \approx 0.48$, that is the optimal tip velocity ratio.

Doubly-fed wind turbine generation systems include wind turbines, transmission systems, generators and the power grid. The turbines capture the energy of the wind and convert it into mechanical energy to turn the turbine, which in turn rotates the rotor of the doubly-fed induction motor via a driveline, thus generating electrical energy, which is transmitted to the grid through the converter. The overall structure of the doubly-fed wind turbine generation system is depicted in Figure 3.

According to the dynamic equation of the transmission system [20–22], the mathematical model of the wind turbine generation system can be described as:

$$\begin{aligned}
\frac{d\Omega_r}{dt} &= \left(\frac{D_r}{J_r} + \frac{K_{opt}}{J_r}\Omega_r\right)\Omega_r - \frac{n_b}{J_r}T_h \\
\frac{d\Omega_g}{dt} &= -\frac{D_g}{J_g}\Omega_g + \frac{1}{J_g}T_h - \frac{1}{J_g}T_g \\
\frac{dT_h}{dt} &= \frac{1}{n_b}\left(K_{ls} - \frac{D_r D_{ls}}{J_r} + \frac{D_{lse}K_{opt}}{J_r}\Omega_r\right)\Omega_r - \frac{1}{n_b^2}\left(K_{ls} - \frac{D_g D_{ls}}{J_g}\right)\Omega_g - D_{ls}\left(\frac{1}{J_r} + \frac{1}{n_b^2 J_g}\right)T_h + \frac{D_{ls}}{n_b^2 J_g}T_g \\
\frac{dT_g}{dt} &= -\frac{1}{\tau_g}T_g + \frac{1}{\tau_g}T_{g,ref}
\end{aligned} \tag{26}$$

where: $K_{opt} = 0.5\rho\pi R^5 C_{p\max}/\lambda_{opt}^2$, D_r and D_g denote the damping coefficients of the rotor and generator respectively, D_{ls} denotes equivalent damping coefficient of low speed shaft; τ_g denotes the time constant of the model; K_{ls} denotes the stiffness coefficient of the equivalent low-speed shaft; J_r denotes the moment of inertia of the rotor shaft of a wind turbine; T_h denotes the high-speed shaft torque; J_g

denotes the moment of inertia of the generator rotor; T_g denotes the electromagnetic torque of the generator; $T_{g,ref}$ denotes the reference value of the electromagnetic torque; n_b denotes the gearshift ratio; Ω_g denotes the rotor speed of the generator.

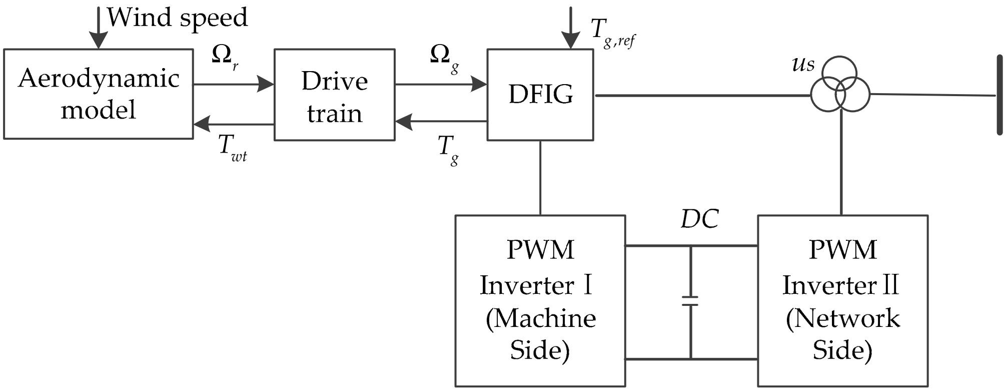


Figure 3. Overall structure of the doubly-fed wind turbine generation system, where u_s is the grid voltage, Ω_r denotes the mechanical angular velocity of the wind turbine, Ω_g denotes the rotor speed of the generator, T_{wt} denotes the output torque of the wind turbine, T_g denotes the electromagnetic torque of the generator, $T_{g,ref}$ represents the reference value of the electromagnetic torque.

By deforming Equation (27), the standard form of wind energy conversion system state equation can be obtained:

$$\begin{aligned} \dot{x}(t) &= A(x)x(t) + Bu(t) \\ y(t) &= C(x)x(t) \end{aligned} \tag{27}$$

where $x(t) = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 \end{bmatrix}^T = \begin{bmatrix} \Omega_r & \Omega_g & T_h & T_g \end{bmatrix}^T$, $u(t) = T_{g,ref}$.

$$A(x) = \begin{bmatrix} (\frac{D_r}{J_r} + \frac{K_{opt}}{J_r}\Omega_r) & 0 & -\frac{n_b}{J_r} & 0 \\ 0 & -\frac{D_g}{J_g} & \frac{1}{J_g} & -\frac{1}{J_g} \\ a_1 + \frac{D_{lse}K_{opt}}{n_b J_r}\Omega_r & a_2 & a_3 & \frac{D_{ls}}{n_b^2 J_g} \\ 0 & 0 & 0 & -\frac{1}{\tau_g} \end{bmatrix}, B = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{\tau_g} \end{bmatrix}, C(x) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$y(t) = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \Omega_r \\ \Omega_g \end{bmatrix}, a_1 = \frac{1}{n_b}\left(K_{ls} - \frac{D_r D_{ls}}{J_r}\right), a_2 = -\frac{1}{n_b^2}\left(K_{ls} - \frac{D_g D_{ls}}{J_g}\right), a_3 = -D_{ls}\left(\frac{1}{J_r} + \frac{1}{n_b^2 J_g}\right)$$

5.2. T-S Fuzzy Modeling of Doubly-Fed Wind Turbine Generation System

T-S fuzzy is carried out for the doubly-fed wind turbine generation system. By observing the system matrix $A(x)$, the fuzzy premise variables $z_1(t) = \Omega_r$ and $z_2(t) = \Omega_g$ are selected, then the membership functions of $z_1(t)$ and $z_2(t)$ are defined $A(x) = \sum_{i=1}^{r} u_i(z(t))A_i$,$B(x) = \sum_{i=1}^{r} u_i(z(t))B_i$, $C(x) = \sum_{i=1}^{r} u_i(z(t))C_i$. For simplification, the membership functions of the two fuzzy subsets can be represented by Equations (28) and (29), where $z_1(t) \in [z_{1\max}\ z_{1\min}]$ and $z_2(t) \in [z_{2\max}\ z_{2\min}]$:

$$F_1(z_1(t)) = \frac{z_1(t) - z_{1\min}}{z_{1\max} - z_{1\min}},\ \overline{F}_1(z_1(t)) = 1 - F_1(z_1(t)) = \frac{z_{1\max} - z_1(t)}{z_{1\max} - z_{1\min}} \tag{28}$$

$$F_2(z_2(t)) = \frac{z_2(t) - z_{2\min}}{z_{2\max} - z_{2\min}},\ \overline{F}_2(z_2(t)) = 1 - F_2(z_2(t)) = \frac{z_{2\max} - z_2(t)}{z_{2\max} - z_{2\min}} \tag{29}$$

The membership functions of $z_1(t)$ is shown in Figure 4, and the membership functions of $z_2(t)$ can be implemented in the same manner.

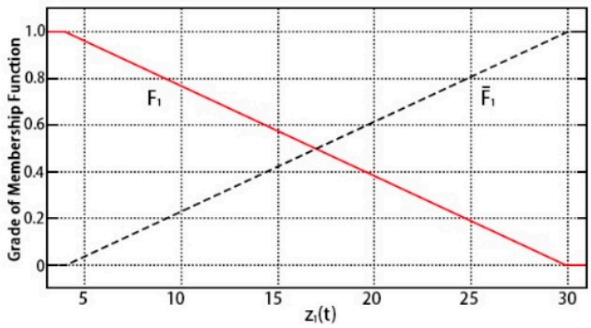


Figure 4. The membership functions.

The fuzzy rules of the T-S fuzzy model with uncertain parameters of wind turbine generation system (26) are given by:

Rule R^i : if $z_1(t)$ is F_1^i and $z_2(t)$ is F_2^i, then:

$$\begin{aligned} &\dot{x}(t) = (A_i + \Delta A_i)x(t) + (B_i)u(t) \\ &y(t) = C_i x(t) \qquad i = 1,2,3,4 \end{aligned} \tag{30}$$

After defuzzification, the equation of state of the whole fuzzy T-S system can be obtained:

$$\begin{aligned} &\dot{x}(t) = \sum_{i=1}^{4} u_i(z(t))[(A_i + \Delta A_i)x(t) + B_i u(t)] \\ &y(t) = \sum_{i=1}^{4} u_i(z(t))C_i x(t) \qquad i = 1,2,3,4 \end{aligned} \tag{31}$$

where:

$$A_i + \Delta A_i = \begin{bmatrix} (\frac{D_r}{J_r} + \frac{K_{opt}}{J_r} z_{1i}) & 0 & -\frac{n_b}{J_r} & 0 \\ 0 & -\frac{D_g}{J_g} & \frac{1}{J_g} & -\frac{1}{J_g} \\ a_1 + \frac{D_{lse}K_{opt}}{n_b J_r} z_{1i} & a_2 & a_3 & \frac{D_{ls}}{n_b^2 J_g} \\ 0 & 0 & 0 & -\frac{1}{\tau_g} \end{bmatrix}, B_i = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{\tau_g} \end{bmatrix}, C_i = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Then the total state feedback controller can be produced:

$$u(t) = r(t) - \sum_{j=1}^{4} u_j(g(t))K_j \hat{x}(t) \tag{32}$$

6. Simulation Results and Analysis

The simulation parameters of the doubly-fed wind turbine generation system in this paper are set as shown in Table 1.

In this paper, the sudden fault of the speed sensor of doubly-fed wind generator is described by the deviation fault. The sensor fault is taken as a function of time t, a deviation signal is applied to the output of the high-speed shaft motor speed sensor between $t = 40$ s and $t = 80$ s, as depicted in Figure 5. The sudden change of the motor speed sensor results in the change of the sensor gain, and the system output can be obtained from Equation (4):

$$y(t) = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \Omega_{r.mes}(k) \\ \Omega_{g.mes}(k) \end{bmatrix} = (I + F)\begin{bmatrix} \Omega_r(k) \\ \Omega_g(k) \end{bmatrix} \tag{33}$$

where $\Omega_{r.mes}(k)$ denotes the measured value of wind turbine speed and $\Omega_{g.mes}(k)$ denotes the measured value of the generator speed, $F = diag(f_1, f_2)$, $f_1, f_2 \in [-0.1, 0.1]$ defines the proportional deviation, I is the identity matrix, $(I + F)$ is the sensor gain.

Table 1. Simulation Parameters.

Parameter Names	Values
Rated power P_n	6 kW
Rated voltage V_s	220 V
Rated speed w_s	100 πrad/s
Air density ρ	1.25 kg/m^3
Blade length R	2.5 m
Transmission efficiency η	0.95
Pole pairs p	2
Rated electromagnetic torque T_g	40 N · m
Inertia of the generator J_g	0.0092kg · m^2
Inertia of the rotor J_r	3.6 kg · m^2

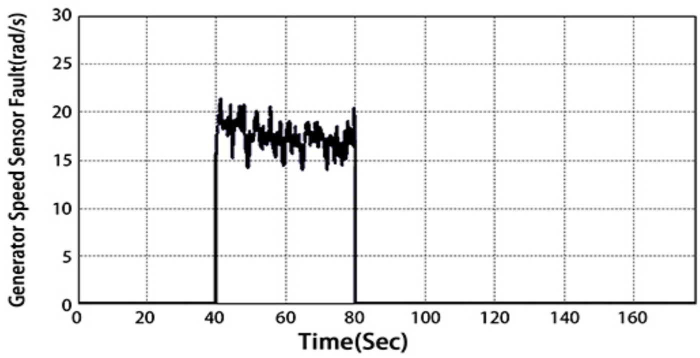


Figure 5. Added generator speed sensor fault signal.

Considering the parameter uncertainty of the system $J_r + \Delta J_r$, Let ΔJ_r change within 20% of the normal value. The variation of uncertainty parameter $J_r + \Delta J_r$ is shown in Figure 6.

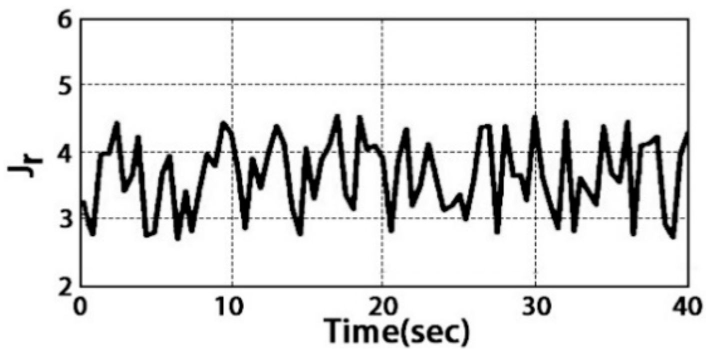


Figure 6. Variation of uncertain parameters $J_r + \Delta J_r$.

Assuming that only one sensor fails at any time, the given wind speed input sequence is shown in Figure 7.

Figure 8 shows the comparison of the estimated value and the actual value of the low-speed shaft speed state Ω_r and high-speed shaft speed state Ω_g when the generator speed sensor fault free. In Figure 9a shows the comparison between the estimated value and the actual value of the low-speed shaft speed state when the system sensor fails, Figure 9b is the comparison diagram between the estimated value and the actual value of the high-speed shaft speed state when the system sensor fails. It is easy to see from Figure 9 between $t = 40$ s and $t = 80$ s, when the motor speed sensor of the high-speed shaft fails, both the low-speed shaft and high-speed shaft speed of the system have sudden changes and the oscillation amplitude increases. However, T-S fuzzy observer can still track the original state of the system quickly and achieve satisfactory state estimation during sensor faults.

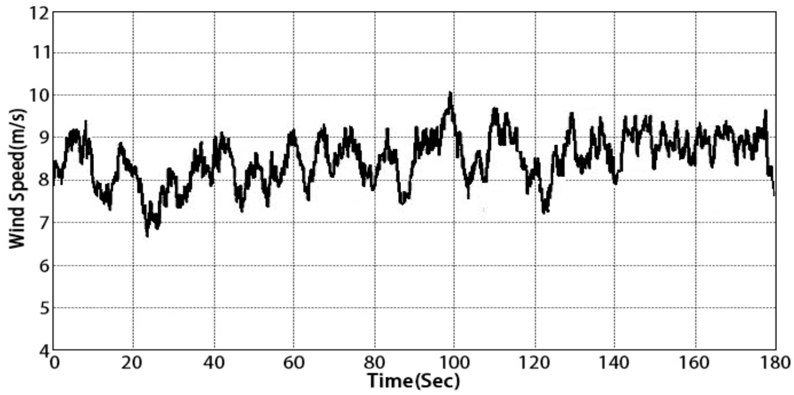
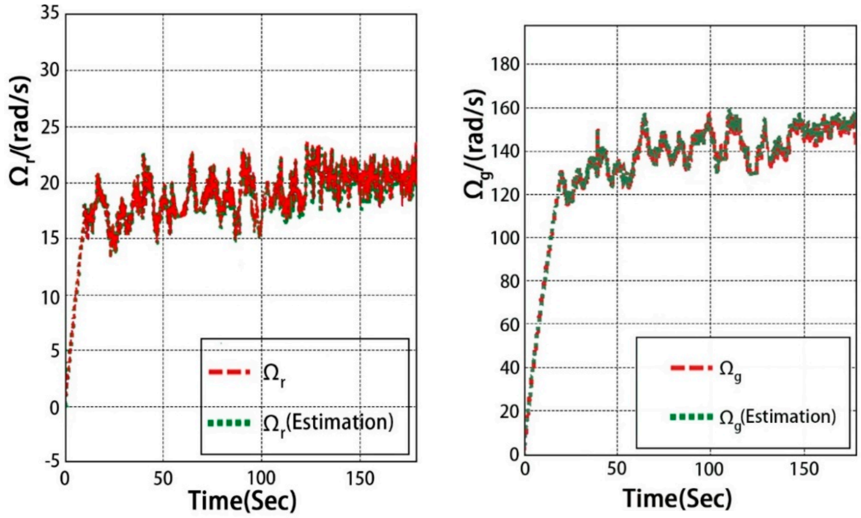


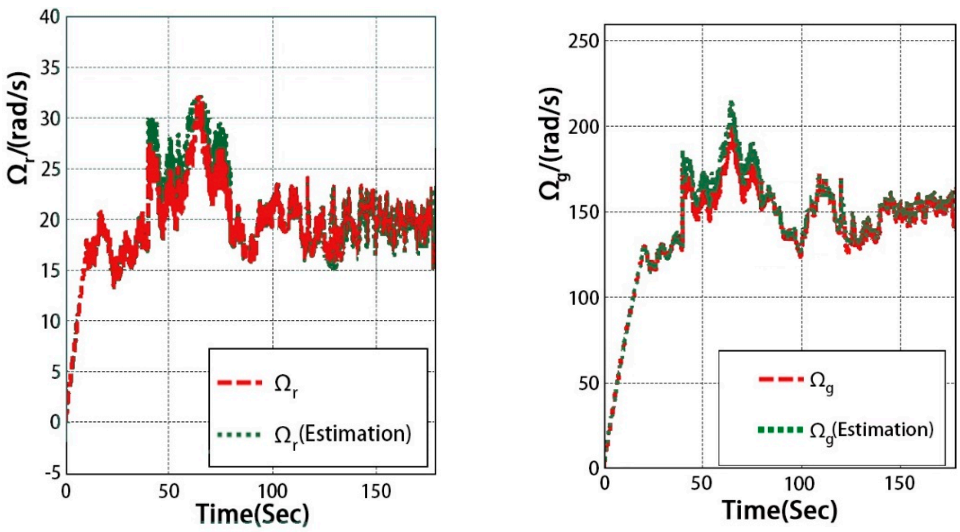
Figure 7. The wind speed V.



(**a**) (**b**)

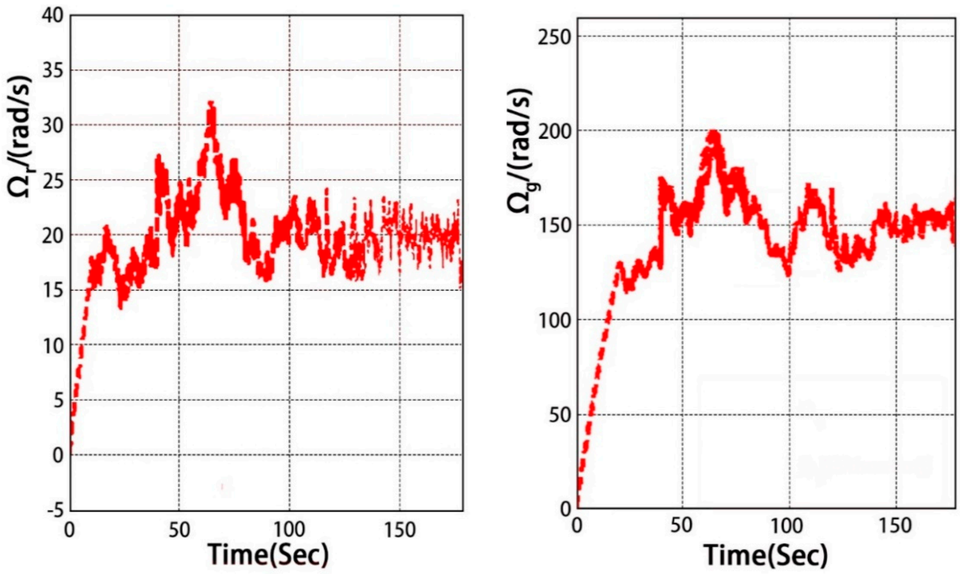
Figure 8. (**a**) Ω_r and its estimated trajectory when the generator speed sensor fault free; (**b**) Ω_g and its estimated trajectory when the generator speed sensor fault free.

Figure 10 shows the operation conditions of the system state when the traditional fuzzy PID controller [17] is adopted in case of sensor failure between $t = 40 \sim 80$ s. By comparing Figures 8 and 9, It can be seen that the trajectories of Ω_r and Ω_g is still seriously deviated from the optimal value and it is difficult to achieve optimal compensation control.



(**a**) (**b**)

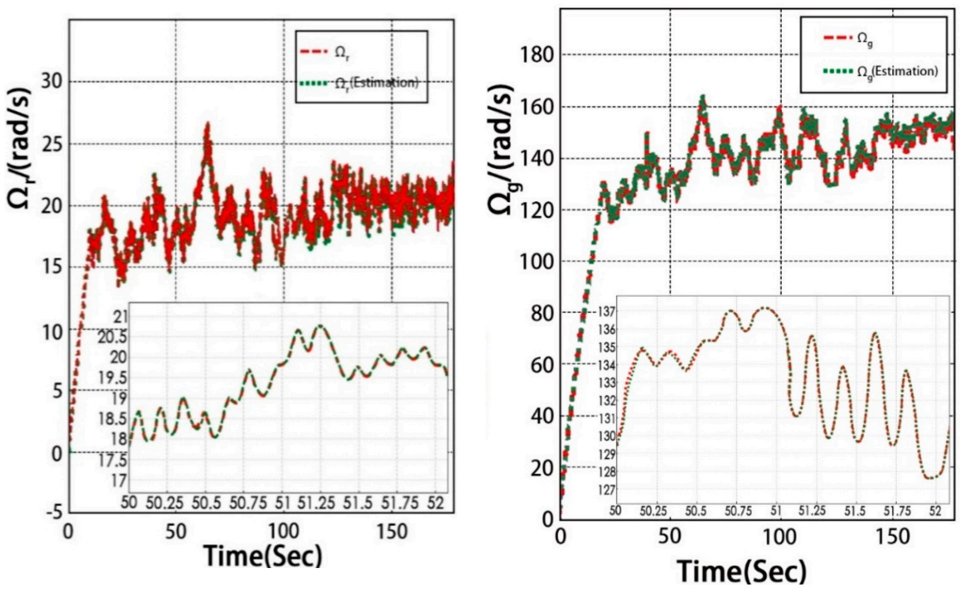
Figure 9. (**a**) Ω_r and its estimated trajectory when the generator speed sensor failure; (**b**) Ω_g and its estimated trajectory when the generator speed sensor failure.



(**a**) (**b**)

Figure 10. (**a**) The trajectories of Ω_r with the fuzzy PID control strategy; (**b**) The trajectories of Ω_g with the fuzzy PID control strategy.

Figure 11 gives the operation of the system's low-speed shaft speed and high-speed shaft speed, and their enlargement between $t = 50 \sim 52$ s by adopting the designed robust fuzzy control strategy when sensor faults occur in the system. As can be seen from the comparison between Figures 10 and 11, between $t = 40\sim 80$ s the robust fuzzy controller designed during the sensor fault can significantly reduce the fluctuation range of the low-speed shaft and high-speed shaft speed, reduce the impact and vibration of the system caused by sensor fault, improve the robustness of the system, and achieve a better fault-tolerant control effect.



(**a**) (**b**)

Figure 11. (**a**) The trajectories of Ω_r with the robust fuzzy control strategy; (**b**) The trajectories of Ω_g with the robust fuzzy control strategy.

The study find that the proposed control strategy in the uncertain value of less than 50% has good fault tolerance effect, after that with the increase of the uncertainty parameter, the designed robust fuzzy controller is more and more difficult to compensate the effects of wind turbine generation system for sensor fault, for how to optimize the design of robust fuzzy controller to achieve better fault-tolerant control system performance will be the focus of our next research.

7. Conclusions

The problem of sensor fault tolerance control in wind turbine generation systems is studied in this paper by establishing an uncertain nonlinear system model with T-S fuzzy theory. Considering the uncertainty of nonlinear systems, the design method of a T-S fuzzy observer for fuzzy systems is presented. Meanwhile, FDI and a robust fuzzy controller are designed based on the T-S fuzzy observer. By using Lyapunov stability theory, the system stability is proved. Finally, it can be seen from the simulation results that when sensor faults occur in the wind turbine generation system, the designed fault-tolerant control method can effectively reduce the impact and oscillation caused by these faults in the system. The robustness of the system is improved to ensure the safe and stable operation of the system under fault, and the fault-tolerant control purpose of sensor fault is realized.

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