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Adaptive Fault Diagnosis and Active Tolerant Control for Wind Energy Conversion System

Zhong-Qiang Wu*, Yang Yang, and Chun-Hua Xu

Abstract: The fault mathematic model of the transmission part of wind energy conversion system (WECS) is established, and adaptive fault observer is constructed in the presence of unknown disturbance, it can detect the faults of the system, and estimate these faults. Then, based on fault observer, an active tolerant controller is designed to ensure the stability of the transmission part of WECS with fault .The simulation results of different type faults of generator show the effectiveness and feasibility of adaptive fault diagnosis methods.

Keywords: Adaptive observer, fault detection and diagnosis, fault tolerant control, wind energy conversion system.

1. INTRODUCTION

In the last few years, with global warming and energy crisis, the development and utilization of new energy have been explored in many countries. Wind energy is a renewable energy sources, and does not produce harmful substances to the environment in the utilizing. In addition, there are abundant wind energy resources on Earth. Therefore, it has become a new power generation sources in many countries around the world.

During wind energy conversion system operating, the transmission system has high possibility of fault. Transmission system is mainly components of the wind turbine, the transmission equipment and the mechanical part of the generator, whose function is transmitting torque to the generator. Now most research works of wind farm only focus on oil temperature detection for transmission system, it is difficult to meet the requirement of the fault diagnosis of WECS based on model.

Currently, the fault diagnosis of wind power system based on the model has attracted many scholars' attention [1]. Manuel *et al*. completed sensor fault detection and isolation of wind energy conversion system (WECS) by the generalized observer [2]. In [3], Liu proposed a local mean decompose method for wind turbine, through iteration demodulating the amplitude and frequency of fault signal so as to control fault system. Anurat adopted states monitoring to realize fault detection and isolation for wind energy conversion system [4]. In [5], the method of support vector machine has been used, and the characteristic parameters of various states of wind generator as learning samples. In the SVM training, in order to achieve fault diagnosis of wind energy conversion system, the mapping relations between different fault types and characteristic parameter vector are established. Many intelligent control algorithms have been studied and applied to fault diagnosis of WECS. In [6], BP neural network based on particle swarm optimization algorithm is used to diagnosis the fault of gearbox of WECS, through the particle swarm algorithm to make up for the deficiency of BP neural network and to improve the robustness of system. In [7], fuzzy control is adopted for fault diagnosis, through establishing the fault tree of system to solve the uncertainty problem of pitch control system, the rapidity and accuracy of the control system is improved. In [8], Expert system for the fault diagnosis of the gearbox of wind energy conversion system is proposed. Furthermore, artificial neural networks method for the fault diagnosis of WECS is proposed, it combined various neural networks to diagnosis the short circuit fault of generator [9]. The above methods have their own advantages, however, the problems of unknown disturbance have not considered. Because the running environment is harsh and many unknown disturbances exist [10], the method of fault diagnosis of WECS should have robustness; when there is an external disturbance, the system can run normally.

In this paper, a robust adaptive observer is designed for wind energy conversion system. It can estimate the fault accurately when there are unknown disturbances in the system. So it can make the output error not sensitive to unknown disturbance. Then based on fault observer, an active tolerant controller is designed to ensure the stability of WECS with fault. The simulation results show the effectiveness and feasibility of adaptive fault diagnosis method and active tolerant controller.

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Zhong-Qiang Wu, Yang Yang, and Chun-Hua Xu are with the College of Electrical Engineering, Yanshan University, Qinhuang dao, Hebei 066004, P. R. China (e-mails: {mewzq, yangyangyang 6380, muzhiqinghan}@163.com).
* Corresponding author.

2. FAULT MATHEMATIC MODEL OF WIND ENERGY CONVERSION SYSTEM

The mathematic model of wind energy conversion system with variable-speed and fixed-paddle can be written as follows (see [11]):

$$\begin{bmatrix}\dot{\omega}_r\\ \dot{\omega}_g\\ \dot{\theta}_\Delta\end{bmatrix}=\begin{bmatrix}-\dfrac{(B_{dt}+B_r)}{J_r} & \dfrac{B_{dt}}{N_gJ_r} & -\dfrac{K_{dt}}{J_r}\\ \dfrac{\eta_{dt}B_{dt}}{N_gJ_g} & \dfrac{-\dfrac{\eta_{dt}B_{dt}}{N_g^2}-B_g}{J_g} & \dfrac{\eta_{dt}K_{dt}}{N_gJ_g}\\ 1 & -\dfrac{1}{N_g} & 0\end{bmatrix}\begin{bmatrix}\omega_r\\ \omega_g\\ \theta_\Delta\end{bmatrix}$$

$$+\begin{bmatrix}\dfrac{T_r}{J_r}\\ 0\\ 0\end{bmatrix}+\begin{bmatrix}0\\ -\dfrac{T_g}{J_g}\\ 0\end{bmatrix},\quad y=\begin{bmatrix}0 & 1 & 0\end{bmatrix}\begin{bmatrix}\omega_r\\ \omega_g\\ \theta_\Delta\end{bmatrix},\tag{1}$$

where ω_γ is rotor speed of wind turbine, ω_g is rotor speed of generator, θ_Δ is torsion angle of transmission system, J_r and J_g is the inertia of the rotor and generator respectively. K_{dt} is torsion stiffness, B_{dt}, B_g and B_r is the inherent damping of torque (torsion), generator and turbine respectively, N_g is the speed increasing ratio of the gearbox. η_{dt} is the efficiency of transmission system, T_r and T_g is the torque of the rotor and generator respectively.

Supposing the generator is constant magnetic flux and the torque is exactly below $T_{g\max}$, non-linear generator torque can be approximate linearized into:

$$T_g = B_g(\omega_g-\omega_z)$$

where ω_z is rotor speed of zero torque.

In the process of system operation, there will be various uncertain factors such as disturbance and system fault, the fault model of system can be written as follows;

$$\begin{cases}\dot{\boldsymbol{x}}(t)=\boldsymbol{Ax}(t)+\boldsymbol{Bu}(t)+\boldsymbol{Ef}(t)+\boldsymbol{r}(t)+\boldsymbol{\eta}_1(t)\\ y(t)=\boldsymbol{Cx}(t),\end{cases}\tag{2}$$

where $\boldsymbol{B}=\begin{bmatrix}0 & \dfrac{B_g}{J_g} & 0\end{bmatrix}^{\mathrm T}$, $\boldsymbol{C}=\begin{bmatrix}0 & 1 & 0\end{bmatrix}$,

$$\boldsymbol{A}=\begin{bmatrix}-\dfrac{(B_{dt}+B_r)}{J_r} & \dfrac{B_{dt}}{N_gJ_r} & -\dfrac{K_{dt}}{J_r}\\ \dfrac{\eta_{dt}B_{dt}}{N_gJ_g} & \dfrac{-\dfrac{\eta_{dt}B_{dt}}{N_g^2}-2B_g}{J_g} & \dfrac{\eta_{dt}K_{dt}}{N_gJ_g}\\ 1 & -\dfrac{1}{N_g} & 0\end{bmatrix},$$

$\boldsymbol{E}\in\boldsymbol{R}^{3\times3}$, $\boldsymbol{x}(t)=[\omega_r\ \ \omega_g\ \ \theta_\Delta]^T$, $\boldsymbol{u}(t)=\omega_z$,

$\boldsymbol{r}(t)=\begin{bmatrix}\dfrac{T_r}{J_r} & 0 & 0\end{bmatrix}^{\mathrm T}$, $y=\omega_g$, $\boldsymbol{f}(t)\in\boldsymbol{R}^3$

is time-varying unknown fault, and suppose $\boldsymbol{f}(t)$ and its differential is norm bounded $\|\boldsymbol{f}(t)\|\le f_0$, $\|\dot{\boldsymbol{f}}(t)\|\le f_1$. Where $f_0\ge 0$, $f_1\ge 0$; $\boldsymbol{\eta}_1(t)$ is the modeling error or external disturbance vector, and $\|\boldsymbol{\eta}_1(t)\|\le g_1$.

3. DESIGN OF ADAPTIVE FAULT OBSERVER

3.1. The model of adaptive fault observer

The model of adaptive fault observer is:

$$\begin{cases}\dot{\hat{\boldsymbol{x}}}_m=\boldsymbol{A}\hat{\boldsymbol{x}}_m+\boldsymbol{Bu}+\boldsymbol{E}\hat{\boldsymbol{f}}+\boldsymbol{G}(\hat{y}_m-y)+\boldsymbol{r}(t)\\ \hat{y}_m=\boldsymbol{C}\hat{\boldsymbol{x}}_m,\end{cases}\tag{3}$$

where $\hat{\boldsymbol{x}}_m(t)\in\boldsymbol{R}^3$ is the state vector of observer. $\hat{y}_m\in\boldsymbol{R}$ is output of observer. $\hat{\boldsymbol{f}}$ is the estimate of $\boldsymbol{f}$. $\boldsymbol{G}\in\boldsymbol{R}^3$ is observer gain matrix to be designed, and satisfies $(\boldsymbol{A}+\boldsymbol{GC})$ is stable.

When the system without fault and uncertainty factors, Equation (3) can be rewritten as

$$\begin{cases}\dot{\hat{\boldsymbol{x}}}=\boldsymbol{A}\hat{\boldsymbol{x}}+\boldsymbol{Bu}+\boldsymbol{G}(\hat{y}-y)+\boldsymbol{r}(t),\\ \hat{y}=\boldsymbol{C}\hat{\boldsymbol{x}}.\end{cases}\tag{4}$$

Define $\boldsymbol{e}(t)=\hat{\boldsymbol{x}}(t)-\boldsymbol{x}(t)$, $\varepsilon_0(t)=\hat{y}(t)-y(t)$.

By (2) and (4) the observation error and output error equation are obtained

$$\begin{aligned}&\dot{\boldsymbol{e}}(t)=(\boldsymbol{A}+\boldsymbol{GC})\boldsymbol{e}(t)-\boldsymbol{Ef}(t)-\boldsymbol{\eta}_1(t),\\ &\varepsilon_0(t)=\boldsymbol{Ce}(t).\end{aligned}\tag{5}$$

By (5) the threshold of the system output error is defined

$$\|\varepsilon_0\|\le\max_{\omega\ge0}\left\|\boldsymbol{C}(j\omega\boldsymbol{I}-\boldsymbol{A}-\boldsymbol{GC})^{-1}\right\|g_1\triangleq\lambda.\tag{6}$$

Fault detection can be executed as follows:

$$\begin{cases}\|\varepsilon_0\|\le\lambda, & \textit{no fault},\\ \|\varepsilon_0\|>\lambda, & \textit{fault}.\end{cases}\tag{7}$$

3.2. The determine of feedback gain matrix of observer

Assumption 1: Suppose that there exist symmetric positive definite matrix $\boldsymbol{Q}$, $\boldsymbol{P}=\boldsymbol{P}^T$, satisfying the following matrix inequality

$$(\boldsymbol{A}-\boldsymbol{EC})^{\mathrm T}\boldsymbol{P}+\boldsymbol{P}(\boldsymbol{A}-\boldsymbol{EC})\le-\boldsymbol{Q}-2\boldsymbol{C}^{\mathrm T}\boldsymbol{C}.\tag{8}$$

According to Assumption 1 the feedback gain matrix G can be deduced, and meets $(\boldsymbol{A}+\boldsymbol{GC})$ being stable. The deriving process as follows:

By (8) gives $(\boldsymbol{A}-\boldsymbol{EC})^{\mathrm T}\boldsymbol{P}+\boldsymbol{P}(\boldsymbol{A}-\boldsymbol{EC})+2\boldsymbol{C}^{\mathrm T}\boldsymbol{C}\le-\boldsymbol{Q}$. Transforming the left of the inequality as:

$$\begin{aligned}&(\boldsymbol{A}-\boldsymbol{EC})^{\mathrm T}\boldsymbol{P}+\boldsymbol{P}(\boldsymbol{A}-\boldsymbol{EC})+2\boldsymbol{C}^{\mathrm T}\boldsymbol{C}\\ &=[\boldsymbol{A}+(\boldsymbol{P}^{-1}\boldsymbol{C}^{\mathrm T}-\boldsymbol{E})\boldsymbol{C}]^{\mathrm T}\boldsymbol{P}\end{aligned}$$

$$+\boldsymbol{P}[\boldsymbol{A}+(\boldsymbol{P}^{-1}\boldsymbol{C}^{\mathrm{T}}-\boldsymbol{E})\boldsymbol{C}]$$
$$\le -\boldsymbol{Q}.$$

If $\boldsymbol{G}=\boldsymbol{P}^{-1}\boldsymbol{C}^{\mathrm{T}}-\boldsymbol{E}$, yield to

$$(\boldsymbol{A}+\boldsymbol{GC})^{\mathrm{T}}\boldsymbol{P}+\boldsymbol{P}(\boldsymbol{A}+\boldsymbol{GC})\le -\boldsymbol{Q}. \tag{9}$$

According to Lyapunov stable theory, if there exists symmetric positive definite matrix $\boldsymbol{P}$, $\boldsymbol{Q}$, satisfy (9), then $(\boldsymbol{A}+\boldsymbol{GC})$ is stable. So the feedback gain matrix of observer is $\boldsymbol{G}=\boldsymbol{P}^{-1}\boldsymbol{C}^{\mathrm{T}}-\boldsymbol{E}$.

3.3. The adaptive estimation of fault

For the estimation of fault, the following assumption is needed.

Assumption 2: For any positive scalar $c>0$ and positive semidefinite matrix $\boldsymbol{S}$, the following inequality holds [12,13]

$$2\boldsymbol{w}^{\mathrm{T}}\boldsymbol{S}\boldsymbol{v}\le (1/c)\boldsymbol{w}^{\mathrm{T}}\boldsymbol{S}\boldsymbol{w}+c\boldsymbol{v}^{\mathrm{T}}\boldsymbol{S}\boldsymbol{v}, \tag{10}$$

where $\boldsymbol{w}\in\boldsymbol{R}^{\mathrm{n}}$, $\boldsymbol{v}\in\boldsymbol{R}^{\mathrm{n}}$.

Define $\boldsymbol{e}_{\mathrm{m}}=\hat{\boldsymbol{x}}_{\mathrm{m}}-\boldsymbol{x}$, $\tilde{\boldsymbol{f}}=\hat{\boldsymbol{f}}-\boldsymbol{f}(t)$.

By (2) and (3) the dynamic equations of the estimation error and output error are described by

$$\begin{aligned}\dot{\boldsymbol{e}}_{\mathrm{m}}&=(\boldsymbol{A}+\boldsymbol{GC})\boldsymbol{e}_{\mathrm{m}}+\boldsymbol{E}\tilde{\boldsymbol{f}}-\boldsymbol{\eta}_1(t),\\ \varepsilon&=\hat{y}_{\mathrm{m}}-y=\boldsymbol{C}\boldsymbol{e}_{\mathrm{m}}.\end{aligned} \tag{11}$$

Using σ correction method in adaptive control (see [14]), the adaptive estimation of fault is

$$\frac{d\hat{\boldsymbol{f}}(t)}{dt}=-\boldsymbol{K}\boldsymbol{\Phi}\varepsilon(t)-\sigma\boldsymbol{K}\hat{\boldsymbol{f}}(t), \tag{12}$$

where $\sigma>0$ is a scalar, $\boldsymbol{K}\in\boldsymbol{R}^{3\times 3}$ and $\boldsymbol{K}=\boldsymbol{K}^{\mathrm{T}}>0$ $\boldsymbol{\Phi}\in\boldsymbol{R}^{3}$, the learning rate of (12) is defined.

If the design of the adaptive diagnosis algorithm can ensure the system described by (11) and (12) asymptotically stable, then the system state and fault estimation error is bounded, and the accurate estimation of the state and fault can be got.

Proof: Choosing a possible Lyapunov function

$$V(t)=e_{\mathrm{m}}^{\mathrm{T}}\boldsymbol{P}e_{\mathrm{m}}+\tilde{\boldsymbol{f}}^{\mathrm{T}}\boldsymbol{K}^{-1}\tilde{\boldsymbol{f}}. \tag{13}$$

Then

$$\begin{aligned}\dot{V}(t)&=\dot{\boldsymbol{e}}_{\mathrm{m}}^{\mathrm{T}}\boldsymbol{P}\boldsymbol{e}_{\mathrm{m}}+\boldsymbol{e}_{\mathrm{m}}^{\mathrm{T}}\boldsymbol{P}\dot{\boldsymbol{e}}_{\mathrm{m}}+\dot{\tilde{\boldsymbol{f}}}^{\mathrm{T}}\boldsymbol{K}^{-1}\tilde{\boldsymbol{f}}+\tilde{\boldsymbol{f}}^{\mathrm{T}}\boldsymbol{K}^{-1}\dot{\tilde{\boldsymbol{f}}}\\ &=e_{\mathrm{m}}^{\mathrm{T}}\left[(\boldsymbol{A}+\boldsymbol{GC})^{\mathrm{T}}\boldsymbol{P}+\boldsymbol{P}(\boldsymbol{A}+\boldsymbol{GC})\right]\boldsymbol{e}_{\mathrm{m}}+2e_{\mathrm{m}}^{\mathrm{T}}\boldsymbol{PE}\tilde{\boldsymbol{f}}\\ &\quad-2e_{\mathrm{m}}^{\mathrm{T}}\boldsymbol{P}\boldsymbol{\eta}_1-2\tilde{\boldsymbol{f}}^{\mathrm{T}}\boldsymbol{\Phi}^{\mathrm{T}}\varepsilon(t)\\ &\quad-2\sigma\tilde{\boldsymbol{f}}^{\mathrm{T}}(\tilde{\boldsymbol{f}}+\boldsymbol{f})-2\tilde{\boldsymbol{f}}^{\mathrm{T}}\boldsymbol{K}^{-1}\dot{\boldsymbol{f}}.\end{aligned}$$

According to Assumptions 1 and 2, we get

$$\dot{V}\le -a_1\|\boldsymbol{e}_{\mathrm{m}}\|^2-a_2\left\|\tilde{\boldsymbol{f}}\right\|^2+b_1, \tag{14}$$

where

$$a_1=\lambda_{\min}(\boldsymbol{Q})-h\lambda_{\max}(\boldsymbol{P})>0,$$
$$a_2=\sigma+2\lambda_{\min}(\boldsymbol{\Phi}\boldsymbol{\Phi}^{\mathrm{T}})-\lambda_{\min}(\boldsymbol{K}^{-1})>0,$$
$$b_1=\frac{\lambda_{\max}(\boldsymbol{P})}{h}\|g_1\|^2+(\sigma f_0^2+\lambda_{\min}(\boldsymbol{K}^{-1})f_1^2)>0,\ h>0$$

is a scalar.

From (13)

$$V\le\lambda_{\max}(\boldsymbol{P})\|\boldsymbol{e}_m\|^2+\lambda_{\max}(\boldsymbol{K}^{-1})\left\|\tilde{\boldsymbol{f}}\right\|^2.$$

Then $\dot{\boldsymbol{V}}\le -\tau\boldsymbol{V}+b_1$,

where $\tau=\dfrac{\min(a_1,a_2)}{\max[\lambda_{\max}(\boldsymbol{P}),\lambda_{\max}(\boldsymbol{K}^{-1})]}$,

$$V\ge\frac{\lambda_{\min}(\boldsymbol{P})}{\|\boldsymbol{C}\|}\|\boldsymbol{\varepsilon}\|^2+\lambda_{\min}(\boldsymbol{K}^{-1})[\left\|\hat{\boldsymbol{f}}\right\|^2-f_0^2].$$

If $(\varepsilon,\hat{\boldsymbol{f}})\in N$, $N=\left\{\boldsymbol{\varepsilon}(t),\hat{\boldsymbol{f}}(t)\left|\dfrac{\lambda_{\min}(\boldsymbol{P})}{\|\boldsymbol{C}\|}\|\boldsymbol{\varepsilon}\|^2+\lambda_{\min}(\boldsymbol{K}^{-1})\left\|\hat{\boldsymbol{f}}\right\|^2\right.\right.$ $\left.>\lambda_{\min}(\boldsymbol{K}^{-1})f_0^2+\dfrac{b_1}{\tau}\right\}$, we can get $V\ge\dfrac{b_1}{\tau}$, and then $\dot{V}<0$.

The error system is asymptotically stable. So the designed of adaptive fault diagnosis algorithm can obtain accurate estimation of the state and fault.

4. DESIGN OF FAULT-TOLERANT CONTROLLER BY STATE FEEDBACK

To design the fault-tolerant controller by state feedback, a useful assumption is given.

Assumption 3: The boundary functions

$$\left\|\boldsymbol{x}^{\mathrm{T}}\boldsymbol{H}\boldsymbol{\eta}(t)\right\|\le\Gamma(\boldsymbol{x},t).$$

Function $\Gamma(\boldsymbol{x},t)/[\|\boldsymbol{x}^{\mathrm{T}}\boldsymbol{HB}\|]$ is continuous and locally bounded on $\boldsymbol{x}$, where $\boldsymbol{H}=\boldsymbol{H}^{\mathrm{T}}>0$ and satisfy the following Riccati equation

$$\boldsymbol{A}^{\mathrm{T}}\boldsymbol{H}+\boldsymbol{HA}-2\boldsymbol{HBB}^{\mathrm{T}}\boldsymbol{H}+\boldsymbol{W}=0, \tag{15}$$

where $\boldsymbol{W}=\boldsymbol{W}^{\mathrm{T}}>0$.

According to the state of fault system being estimated by the observer, the fault-tolerant controller of fault system need to be designed to ensure the closed-loop stability. The feedback control law is designed as follows

$$\boldsymbol{u}=\boldsymbol{u}_1+\boldsymbol{u}_2, \tag{16}$$

where

$$\boldsymbol{u}_1=-\boldsymbol{B}^{\mathrm{T}}\boldsymbol{H}\hat{\boldsymbol{x}}_{\mathrm{m}}-\bar{\boldsymbol{E}}\hat{\boldsymbol{f}}, \tag{17}$$

$$\boldsymbol{u}_2=-\frac{\boldsymbol{\phi}(\boldsymbol{x},t)}{\|\boldsymbol{\phi}(\boldsymbol{x},t)\|+d/2}\frac{\Gamma(\boldsymbol{x},t)}{\left\|\boldsymbol{x}^{\mathrm{T}}\boldsymbol{HB}\right\|}. \tag{18}$$

With $\boldsymbol{\phi}(\boldsymbol{x},t)=\dfrac{\boldsymbol{B}^{\mathrm{T}}\boldsymbol{Hx}}{\left\|\boldsymbol{x}^{\mathrm{T}}\boldsymbol{HB}\right\|}\Gamma(\boldsymbol{x},t)$, d is a positive scalar and $\boldsymbol{E} = \boldsymbol{B}\bar{\boldsymbol{E}}$.

Substituting control law (16) into transmission system model (2), the following closed-loop state equations of fault system is got

$$\begin{aligned}\dot{\boldsymbol{x}} &= (\boldsymbol{A} - \boldsymbol{B}\boldsymbol{B}^{\mathrm{T}}\boldsymbol{H})\boldsymbol{x} - \boldsymbol{B}\boldsymbol{B}^{\mathrm{T}}\boldsymbol{H}\boldsymbol{e}_{\mathrm{m}} \\ &\quad -\boldsymbol{E}\tilde{\boldsymbol{f}} + \boldsymbol{r}(t) + \boldsymbol{B}\boldsymbol{u}_2 + \boldsymbol{\eta}_1(t).\end{aligned} \tag{19}$$

If the design of the feedback control law can ensure the closed-loop system (19) stability, the active fault tolerant controller designed can guarantee the normal running of the fault system.

Proof: Choosing a possible Lyapunov function

$$\boldsymbol{V}_1 = \boldsymbol{e}_{\mathrm{m}}^{\mathrm{T}}\boldsymbol{P}\boldsymbol{e}_{\mathrm{m}} + \tilde{\boldsymbol{f}}^{\mathrm{T}}\boldsymbol{K}^{-1}\tilde{\boldsymbol{f}} + \beta\boldsymbol{x}^{\mathrm{T}}\boldsymbol{H}\boldsymbol{x},$$

where $\beta > 0$ is a scalar.

$$\begin{aligned}\dot{\boldsymbol{V}}_1 &= \dot{\boldsymbol{e}}_{\mathrm{m}}^{\mathrm{T}}\boldsymbol{P}\boldsymbol{e}_{\mathrm{m}} + \boldsymbol{e}_{\mathrm{m}}^{\mathrm{T}}\boldsymbol{P}\dot{\boldsymbol{e}}_{\mathrm{m}} + \dot{\tilde{\boldsymbol{f}}}^{\mathrm{T}}\boldsymbol{K}^{-1}\tilde{\boldsymbol{f}} + \tilde{\boldsymbol{f}}^{\mathrm{T}}\boldsymbol{K}^{-1}\dot{\tilde{\boldsymbol{f}}} \\ &\quad +\beta\{\boldsymbol{x}^{\mathrm{T}}[\boldsymbol{H}(\boldsymbol{A} - \boldsymbol{B}\boldsymbol{B}^{\mathrm{T}}\boldsymbol{H}) + (\boldsymbol{A} - \boldsymbol{B}\boldsymbol{B}^{\mathrm{T}}\boldsymbol{H})^{\mathrm{T}}\boldsymbol{H}]\boldsymbol{x} \\ &\quad - 2\boldsymbol{x}^{\mathrm{T}}\boldsymbol{H}\boldsymbol{B}\boldsymbol{B}^{\mathrm{T}}\boldsymbol{H}\boldsymbol{e}_{\mathrm{m}} + 2\boldsymbol{x}^{\mathrm{T}}\boldsymbol{H}[\boldsymbol{r}(t) + \boldsymbol{B}\boldsymbol{u}_2 + \boldsymbol{\eta}_1(t)] \\ &\quad - 2\boldsymbol{x}^{\mathrm{T}}\boldsymbol{H}\boldsymbol{E}\tilde{\boldsymbol{f}}\}.\end{aligned}$$

By substitution of (18) yields

$$\begin{aligned}&2\beta\boldsymbol{x}^{\mathrm{T}}\boldsymbol{H}[\boldsymbol{r}(t) + \boldsymbol{B}\boldsymbol{u}_2 + \boldsymbol{\eta}_1(t)] \\ &\le 2\beta\left[\|\boldsymbol{\phi}(\boldsymbol{x},t)\| - \frac{\|\boldsymbol{\phi}(\boldsymbol{x},t)\|^2}{\|\boldsymbol{\phi}(\boldsymbol{x},t)\| + d/2}\right] \le \beta d.\end{aligned}$$

By using the condition (10) and (15), we get $\dot{\boldsymbol{V}}_1 \le -m_1\|\boldsymbol{x}\|^2 - m_2\|\boldsymbol{e}_{\mathrm{m}}\|^2 - m_3\|\tilde{\boldsymbol{f}}\|^2 + \beta d$, we can get the appropriate d to meet

$$\dot{\boldsymbol{V}}_1 \le -m_1\|\boldsymbol{x}\|^2 - m_2\|\boldsymbol{e}_{\mathrm{m}}\|^2 - m_3\left\|\tilde{\boldsymbol{f}}\right\|^2 + \beta d \le 0, \tag{20}$$

where

$$\begin{aligned}&m_1 = \lambda_{\min}(\boldsymbol{S}_1), \\ &\boldsymbol{S}_1 = \beta\boldsymbol{W} - \beta\boldsymbol{H}\left(\boldsymbol{B}\boldsymbol{B}^{\mathrm{T}}/c_1 + \boldsymbol{E}\boldsymbol{E}^{\mathrm{T}}/c_2\right)\boldsymbol{H}, \\ &m_2 = \lambda_{\min}(\boldsymbol{S}_2),\ \boldsymbol{S}_2 = \boldsymbol{Q} - \beta c_1\boldsymbol{H}\boldsymbol{B}\boldsymbol{B}^{\mathrm{T}}\boldsymbol{H},\ m_3 = 2 - \beta c_2.\end{aligned}$$

The parameters c_1, c_2 and β are chosen to satisfy the following inequalities

$$\boldsymbol{S}_1 > 0,\quad \boldsymbol{S}_2 > 0,\quad m_3 > 0.$$

According to (20), it is known that the feedback control law (16) can make the closed-loop fault system stable, and ensures the normal running of system when fault occurred.

5. SIMULATION STUDIES

In the simulation, the parameters are as follows:

$$B_{\mathrm{dt}} = 9.45\times 10^5,\quad B_\gamma = 2.78\times 10^4,\quad B_{\mathrm{g}} = 3.034,$$

$$N_{\mathrm{g}} = 95,\quad K_{\mathrm{dt}} = 2.7\times 10^9,\quad \eta_{\mathrm{dt}} = 0.92,\quad J_{\mathrm{g}} = 390,$$

$$J_\gamma = 55\times 10^6,\ T_{\mathrm{r}} = 15.84\times 10^7,\ \boldsymbol{\eta}_1(t) = \begin{bmatrix} 0 \\ rand(0.0015) \\ 0 \end{bmatrix}.$$

Then

$$\boldsymbol{A} = \begin{bmatrix} -1.7687\times 10^{-2} & 1.8096\times 10^{-4} & -49.091 \\ 23.466 & -0.2626 & 6.7045\times 10^4 \\ 1 & -0.0105 & 0 \end{bmatrix},$$

$$\boldsymbol{B} = \begin{bmatrix} 0 \\ 0.0078 \\ 0 \end{bmatrix}.$$

In simulation, only generator fault is considered.

$$\boldsymbol{E} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0.0078 & 0 \\ 0 & 0 & 0 \end{bmatrix},\quad \boldsymbol{\Phi} = [1\quad 1\quad 1]^{\mathrm{T}},$$

we get

$$\boldsymbol{P} = \begin{bmatrix} 534.85 & 4.0122\times 10^{-5} & 9.1878\times 10^{-5} \\ 4.0122\times 10^{-5} & 0.39002 & 6.3807\times 10^{-6} \\ 9.1878\times 10^{-5} & 6.3807\times 10^{-6} & 26256 \end{bmatrix},$$

$$\boldsymbol{G} = \begin{bmatrix} 0.0184 \\ -3.4 \\ 0.0057 \end{bmatrix},$$

$$\boldsymbol{H} = \begin{bmatrix} 1.7245\times 10^8 & -1.2159\times 10^6 & -1.3005\times 10^8 \\ -1.2159\times 10^6 & 32734 & -6.2087\times 10^6 \\ -1.3005\times 10^8 & -6.2087\times 10^6 & 1.0244\times 10^{10} \end{bmatrix}.$$

The fault is as follows $\boldsymbol{f}(t) = [0\quad f_i(t)\quad 0]^{\mathrm{T}}$, $i = 1, 2$ where fault f_1 is supposed the actuator fault of the main transmission chain, and result in constant biases. The fault can be described as follows:

$$\textbf{F1:}\quad f_1(t) = \begin{cases} 0, & 0 < t < 20s \\ 80, & t \ge 20. \end{cases}$$

Fault f_2 is supposed the shaft fault of gear box, and result in double frequency vibrations, the vibrations frequency of shaft is 10Hz. Then, the fault can be described as follows:

$$\textbf{F2:}\quad f_2(t) = \begin{cases} 0, & 0 < t < 20s \\ 160 + 80\sin(125.6t), & t \ge 20s. \end{cases}$$

The simulation results are shown in Figs. 1~6:

Figs. 1 and 2 show the output error when fault $f_1(t)$ and $f_2(t)$ occurred, respectively. The system output error is quickly beyond the threshold when fault accrued; the simulation results show that the observer designed can detect the system fault accurately and rapidly.

Figs. 3 and 4 show the estimation of fault $f_1(t)$ and $f_2(t)$ by the observer designed. The simulation results show that the fault observer designed can estimate the fault accurately, whether it is a constant fault or time-varying fault.

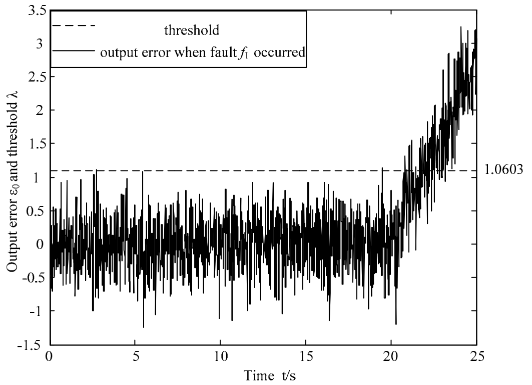

Fig. 1. The detection of fault f_1.

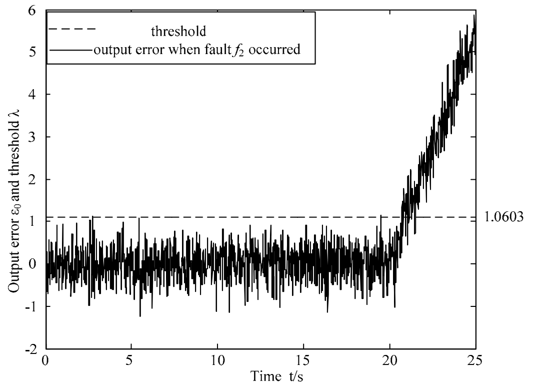

Fig. 2. The detection of fault f_2.

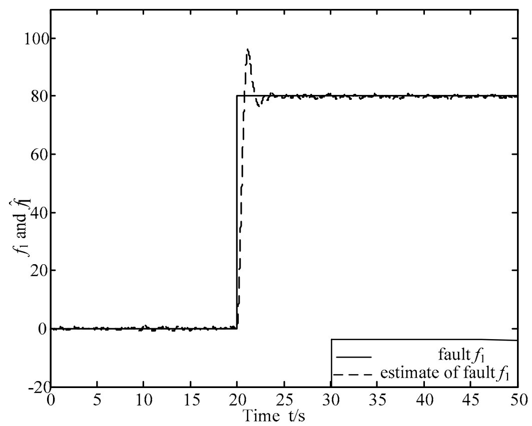

Fig. 3. The fault f_1 and its estimate $\hat{f}_1$.

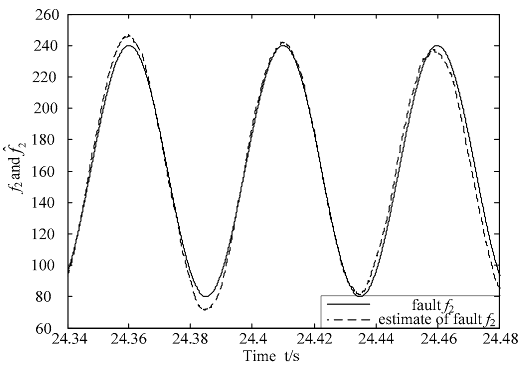

Fig. 4. The fault f_2 and its estimate $\hat{f}_2$.

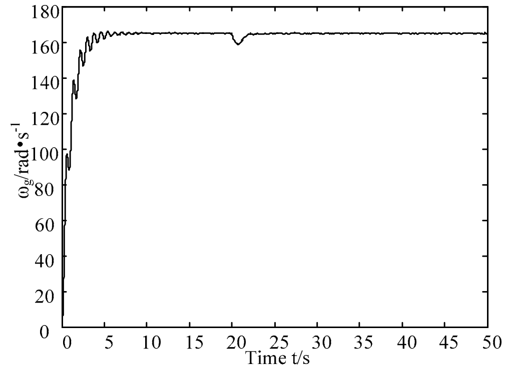

Fig. 5. The fault-tolerant controller output of constant fault occurred.

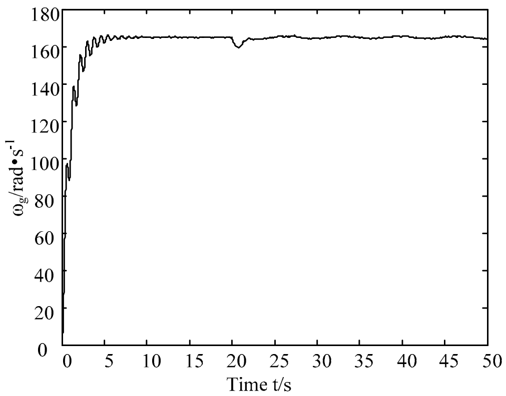

Fig. 6. The fault-tolerant controller output of time - varying fault occurred.

Figs. 5 and 6 show the system output after the active fault-tolerant controller is used when constant fault and time-varying fault occurred, respectively. When fault happened, the results show that fault-tolerant controller can make the system output wave in a smaller range. It is show that the control method has very strong robustness, no matter constant fault or time-varying fault.

In [15], the benchmark model is adopted, which includes hydraulic pitch model, converter model and drive train model, so it is comprehensive. Three kinds of fault have been considered, sensor fault (fixed value or gain factor), actuator fault (offset) and parameter abrupt. Only the parameter abrupt can be estimated by least-square method which needs last N samples of input and output. Sensor and actuator fault are got by measurement or the deference between measured and expected value, so it needs many sensors. The tolerant control corresponding needs auxiliary controllers (it needs to be designed in advance for redundant).

In this paper, only drive train model is considered, and is used to test the effectiveness of control scheme. The fault is estimated by an adaptive mechanism which depends on the model, it can approximate the fault gradually, not need least-square method which needs many samples of input and output, and the number of sensor can be reduced effectively. The fault can be estimated adaptively, auxiliary controllers are not needed. It is simple and suitable for appliance.

6. CONCLUSION

In this paper, a new adaptive fault observer is designed for the transmission part of the wind energy conversion system, in the case of unknown input and disturbance. It can accurately detect and estimate the fault, no matter constant fault or time-varying fault, respectively. Then a state feedback fault-tolerant controller is designed, it can maintain system normal running when a fault occurred. The simulation results show the feasibility and effectiveness of the adaptive fault observer and fault-tolerant controller for wind energy conversion system.

REFERENCES

[1] X.-F. Chen, J.-M. Li, H. Cheng, B. Li, and Z.-J. He, "Research and application of condition monitoring and fault diagnosis technology in wind turbines," *Journal of Mechanical Engineering*, vol. 47, no. 9, pp. 45-52, May 2011.

[2] G. C. Manuel and K. Michel, "Sensor fault detection and isolation in doubly-fed induction generators accounting for parameter variations," *Renewable Energy*, vol. 36, no. 5, pp. 1447-1457, May 2011.

[3] W.-Y. Liu, W. H. Zhang, J. G. Han, and J.-F. Wang, "A new wind turbine fault diagnosis method based on the local mean decomposition," *Renewable Energy*, vol. 48, pp. 411-415, December 2012.

[4] Y. Anurat, M. Benbouzid, E. A1-Alunar, B. Bensaker, and S. Turri, "A brief status on condition monitoring and fault diagnosis in wind energy conversion system," *Renewable and Sustainable Energy Reviews*, vol. 13, no. 9, pp. 2629-2636, December 2009.

[5] X.-L. An, M.-H. Zhao, D.-X. Jiang, and S.-H. Li, "Direct-drive wind turbine fault diagnosis based on support vector machine and multi-source information," *Power System Technology*, vol. 35, no. 4, pp. 117-122, April 2011.

[6] Q. Long, Y.-Q. Liu, and Y.-P. Yang, "Fault diagnosis method of wind turbine gearbox based on BP neural network trained by particle swarm optimization algorithm," *Acta Energiae Solaris Sinica*, vol. 33, no. 1, pp. 120-125, April 2012.

[7] S. He, W.-Q. Wang, X.-Y. Zhan, J. Chen, and H.-Y. Wang, "Short circuit fault intelligent diagnosis of MW permanent magnet wind power generator based on artificial neural network," *Electric Machines & Control Application*, vol. 38, no. 9, pp. 24-29, September 2011.

[8] H. Liu, X.-H. Dong, Z.-L. Yang, and K. Zheng, "The application of intelligent fuzzy inference to the fault diagnosis in pitch-controlled system," *Proc. of International Conference on Future Energy, Environment, and Materials*, pp. 1839-1844, 2012.

[9] Z.-L. Yang, B. Wang, X.-H. Dong, and H. Liu, "Expert system of fault diagnosis for gear box in wind turbine," *Systems Engineering Procedia*, vol. 4, pp. 189-195, April 2012.

[10] C.-S. Zhang, Y.-S. Huang, and R. Shao, "Fault detection method and application of induction motor based on observer," *Chinese Journal of Scientific Instrument*, vol. 32, no. 6, pp. 1337-1343, June 2011.

[11] S. Christoffer, E. Thomas, and S. Jalcob, "Robust and fault-tolerant linear parameter-varying control of wind turbines," *Mechatronics*, vol. 21, no. 4, pp. 645-659, June 2011.

[12] K. Zhang and B. Jiang, "Fault diagnosis observer-based output feedback fault tolerant control design," *Acta Automatica Sinica*, vol. 36, no. 2, pp. 274-281, February 2010.

[13] K. Zhang, B. Jiang, and J.-J. Liu, "Fast fault accommodation of control systems by using adaptive observer," *Control and Decision*, vol. 23, no. 7, pp. 771-775, July 2008.

[14] P. A. Ioannou and J. Sun, *Robust Adaptive Control*, Prentice Hall, Englewood Cliffs, NJ, 1995.

[15] B. Joaquim, R. Damiano, P. Vicenc, and N. Fatiha, "FDI and FTC of wind turbines using the interval observer approach and virtual actuators/sensors," *Control Engineering Practice*, vol. 24, pp. 138-155, March 2014.

Zhong-Qiang Wu received his B.Sc. and M.Sc. degrees in Automatic Control from Northeast Heavy Machinery Institute, P. R. China in 1989 and 1992, respectively, and his Ph.D. degree in Control Theory and Control Engineering from China University of Mining and Technology, P. R. China in 2003. He is a professor at the College of Electrical Engineering Yanshan University, P. R. China. His research interests include intelligent control of wind power system.

Yang Yang received her M.Sc. degree in Control Theory and Control Engineering from the College of Electrical Engineering, Yanshan University, P. R. China in 2013. Her research interests include intelligent control of wind power system.

Chun-Hua Xu received his M.Sc. degree in Control Theory and Control Engineering from the College of Electrical Engineering, Yanshan University, P. R. China in 2014. His research interests include intelligent control of wind power system.